GEOSPATIAL HEALTH EQUITY IN THE US AND INDIA

by
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Dissertation Abstract

Background

Health equity is a public health priority in the US and globally, as people and their governments view large, objectively measurable health disparities through a lens of social justice. Inequities in child and adult mortality rates can result from sustained systems of public health and healthcare provision that favor members of a certain population, often defined by income or race. Characteristics of a community can be associated with health inequities, including environmental factors and the public health amenities provided by local governments. Geospatial inequities can result from the resources available to local governments and the characteristics of their populations. This analysis investigates the extent and trend in such inequities and the role of local governments in their mitigation.

Methods

This thesis adapts the concentration index and concentration curve, established economic measures, to a geospatial context. The Inter-County Concentration Index (ICCI) was used to measure inequities in age-adjusted mortality rates from 1972 to 2012 across the US and within each state. In India, the Inter-District Concentration Index (IDCI) was used to measure inequities in under-five mortality rates in 2001 and 2012. Spatial associations between key variables were measured in both the US and India using Moran's I. To measure the effects of state and county-level expenditures upon state-level inequities in the US, a panel model for 47 states was fitted to data from 1972 to 2012. The effects of state to county intergovernmental transfers were measured, as were the effects of total county spending on social programs.

Results

ICCI was statistically significant for every year in the national-level analysis and there was a significant trend upwards, with all but one concentration curve statistically dominating that of the previous time period. In 2012, 4.2% of mortality would have to be redistributed from low income to high income counties to achieve equality. State and regional level analyses broadly followed similar trends. ICCIs remained significant after adjusting for county level demographic and economic controls. In India, IDCIs were statistically significant of a larger order. In 2012, 10.7% of under-five mortality would have had to be redistributed from poor to wealthier districts to achieve equality. The national level concentration curve for 2012 dominated that of 2001, as did state-level concentration curves in approximately half of the individual states. In the US, state to local transfers were found to reduce state ICCIs over the period of analysis by a small but statistically significant amount and total social spending by county governments increased ICCIs by a larger amount. Results are robust to a wide range of specifications.

Conclusions

Geospatial health inequity, as measured by ICCI and IDCI, has been shown to be statistically significant and increasing in both countries of this analysis. Results must be interpreted in the context of absolute levels of mortality and under-five mortality respectively, as policymakers face a potential trade-off between the efficiency and equity of public health investments. The significant effect of intergovernmental transfers in reducing ICCI demonstrates that governments have the tools to improve equity in their populations. These measures provide a mechanism to include geospatial perspective in health equity discourse and to hold governments accountable for their policies as rich places become healthier and poor places become sicker.

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Chapter 1: Introduction

Background

Despite the progress that has been demonstrated globally in absolute measures of health through the MDGs, health inequity remains a major challenge [1, 2]. There is a considerable body of research into socioeconomic determinants of health outcomes globally with strong associations between income and class related indicators and mortality rates [3, 4, 5]. An inverse relationship between education and adult mortality has been observed in high and low income countries [6, 7]. Health systems consistently provide greater volume and quantity of services to the wealthy than to the poor and this compounds existing health inequity [8]. The resources required to improve health, including provision of public services such as clean water and sanitation are socially determined [7]. The determination of these is a matter of public policy and is often driven by geographical delineations. Wagstaff compared mortality inequalities within nine developing countries and found higher under-5 mortality in the poorest quintile than in others across all countries, with rates generally decreasing with movement up the income distribution. Dominance checking revealed that inequalities found were statistically significant, and highest in countries where overall mortality was lower [9].

Reducing health inequalities by poverty level is a central goal of many governments and international organizations, however mortality disparities in developing countries are large and, in some cases, growing [1]. The 'zero draft' of the Sustainable Development Goals lists "Reduce inequality within and among countries" as its tenth goal [10] however this primarily deals with income inequality. It is unclear whether there is an association between income inequality and mortality. In identifying the diminishing life expectancy returns to national income, Preston theorized that if the same relationship holds within countries then lower income inequality within a country should be reflected in higher life expectancy [11]. Rodgers demonstrated using data from 56 countries that this association exists, finding that higher Gini indices, and other measures, have significant association with lower life expectancy. This is a mathematical artifact of aggregating individual non-linear relationships between income and life expectancy to population level [12]. Empirical evidence, especially in developed countries, has not always supported a significant association [13, 14, 15]. Wilkinson has suggested an individual effect of income inequality on mortality, acting through stress at the individual level [16]. Other factors may also explain some of the additional effect, including environmental and public health interventions.

Sub-national geospatial variation in mortality rates is very clear. The age-adjusted death rate in the US was 731.9 per 100,000 standard population in 2013 [17]. Mortality rates in the US have been reducing significantly, despite the aging of the population and large population increases since 1935. However there are dramatic geospatial disparities, as is clear from a recent study which mapped cause specific mortality rates across the US and found vary large disparities between counties [18]. For example, age-standardized mortality rate from neoplasms, shown in Figure 1.1, ranged from 70.7 deaths per 100,000 population in the county with the lowest rate to 503.1 in the county with the highest. The geospatial contrast in mortality is even more dramatic in India than in the US. India accounts for 21% of all under-five deaths globally, with a U5MR of 53 per 1,000 live births in 2013. this has declined from 126 per 1,000 live births in 1990, an annual reduction rate of 3.8% [19]. 12 out of every 1,000 children born in the state of Kerala die before the age of 5, but in the state of Assam the rate is more than 6 times as high, at 73 per 1,000 live births [20]. A recent study of child mortality rates by district illustrated a wide variation in rates across and within states, shown in Figure 1.2 [21].

These studies highlight the importance of place, defined both geographically and politically, upon cause-specific mortality in the US and upon under-five mortality rate in India. Despite broad awareness of the geospatial disparities in health indicators, and mortality in particular, the study of subnational inequalities has been primarily concerned with inequalities based on individual income and inequalities based on race, ethnicity or tribe with little regard for geospatial differences.

Definitions of health equity draw from the fields of ethics, economics and sociology. The WHO defines health inequalities as "inequalities in health status, risk factors, or health service utilization between individuals or groups, that are unnecessary, avoidable, and unfair" [22]. Health equity is less objectively measurable and relates to the distributive or process justice of health and health services. From an economic perspective, equality has been defined in terms of the equalization of resources, opportunities or outcomes, equality of expenditure per capita on health, distribution of health resources according to need, equality of access to health or healthcare, and equality of health [23]. A distributive justice approach is taken in this research, with life expectancy, all-cause mortality rate and child mortality rate as the primary health outcomes.

A Geospatial Approach to Health Equity

Kindig recently highlighted the insufficiency of current academic discourse on health equity in generating population-wide policy solutions. The emphasis upon high rates among racial minorities, though crucially important to any discussion of inequity, misses the larger burden that a relatively low rate can have in a larger population, and the resource distribution and policy implications of this in addressing overall inequities [24]. This analysis builds upon the argument that one perspective on health inequity is insufficient to understand and address the challenges of health inequity. The social, economic, historic and geographic factors affecting health equity have complex interactions and a single perspective may be insufficient. The choice of definitions for comparison populations when measuring equity limits the conclusions that can be drawn by aggregating other definitions of population [25]. The consideration of multiple types of population reduces the risk of missing important aspects of inequity. For example, Chetty and colleagues [4] went some way to addressing this limitation by disaggregating by both income and commuting zone, based on life expectancy from age 45, and found increasing inequalities in life expectancy with interesting geospatial variation. Currie and Schwandt pointed out that the trends in child mortality were equalizing more quickly between rich and poor counties and found this offset adult mortality inequality [26]. However they grouped counties by income level and did not focus on any geospatial relationships, grouping poor counties without regard to state lines or proximity to each other. The summary measures of geospatial health equity proposed and tested in these papers provide an important additional perspective on health equity and illustrate some particular characteristics of health inequities in the US and India.

Other than providing an additional perspective to researchers and policymakers on health equity, geospatial inequities have distinct characteristics that make them important in their own right. As local governments tailor health amenities to the preferences and income of their populations, and people self-sort to match the amenities provided, inequalities between counties and districts are likely to become more entrenched. As poor areas fail to invest in public amenities the social determinants of health in that area are likely to deteriorate, compounding the stratification and leading to a cycle of inequity [1, 5]. In addition, when tax-funded state and federal systems that subsidize healthcare in retirement exist, such as Medicare, they result in fiscal inequity. If the populations of rich counties live longer than those of poor counties on average, they realize the benefits from such schemes over a longer period hence poor counties are paying more than their share and are, in effect, subsidizing the richer counties. Such fiscal inequities have been discussed in relation to the Scots in Britain and the Walloons in Belgium [27, 28]. There is also evidence of an impact on psychological health of frequent exposure of economically disadvantaged populations to wealthier or visibly advantaged populations, resulting in toxic stress and long term negative effects on the health of such populations [29, 30, 31].

The concentration of health in rich counties and districts is not well understood by researchers, policymakers or citizens. Recognizing health as a human right means accepting that these inequalities are unjust. Citizens and their governments have a role in redistributing health more equitably, but need to be more informed about the extent of geospatial health inequities and the potential tools available to address them. This analysis aims to measure the levels and trends in geospatial health equity in the US and India and the effects of certain types of government expenditure upon inequities over time.

Theoretical Framework

The theoretical framework is based upon the relationship between local government, public health and the characteristics of geospatially-defined populations. In the US county governments have more information about their populations than state and federal government and this allows them to tailor their provision of public amenities, including public health amenities, to the preferences of their constituent populations subject to their budget constraint. This budget constraint is limited by their tax base, which is dependent upon the incomes of the county population. For any given preference for health, counties will stratify by their ability to provide commensurate health amenities, therefore by their income. For any given level of income, counties will stratify based on their preferences for health versus consumption of other goods. This results in sustained health inequities between counties with health indicators, in this case mortality, associated with income. This may be reinforced by a form of Tiebout sorting, through which individuals choose a county based upon their preferences for the health amenities provided and their ability to pay the associated taxes [32, 33]. They migrate between counties to self-sort by income and preferences for public health amenities. The resulting geospatial inequities are therefore self-propagating.

In the application of this framework to India, again districts are limited in the health amenities they can provide by the resources of their populations and this results in large child mortality between districts [21]. Another factor in the case of India is a shortage in human resources for health. Health professionals are migrating to more urban and wealthier districts, probably due to opportunities for their scarce skills in a form of 'brain drain' and the growth of private sector services relative to public sector health services [34, 35]. This has resulted in far fewer health workers in poor and rural areas, and in particular fewer qualified health professionals in these areas [36, 37]. These geospatial changes to healthcare access are likely to reinforce the health inequities that exist between districts, especially with regard to infant and child health.

A final theoretical pillar for this dissertation is the association of state to county government transfers for the geospatial redistribution of health in the US. There is evidence that the decentralization of resource control from state to local level is effective in improving local health outcomes in the US and elsewhere [38, 39, 40]. Local governments use their own resources for the benefit of their own population, therefore higher income districts can provide more and better amenities than their less resourced counterparts, resulting in geospatial inequities. State transfers can be used to supplement the resources of poorer counties, partially offsetting resource imbalances and hence reducing health inequities.

Overview of Analyses

Paper 1 applies a geospatial measure of mortality inequity in the US and measures these inequities every 5 years between 1972 and 2012. All-cause age-adjusted mortality is compared across counties, based on its relationship with median county income. The primary measure used is a county-level version of the concentration index. Statistical significance of inter-county inequity is measured at each time point, as is its relationship to the previous level using statistical dominance of concentration curves. Several methods of measuring inequity are compared to assess the robustness of this method in producing a summary measure. The analysis is then repeated at state level to measure intra-state inequities. The measure of inequity is adjusted for several state demographic characteristics to decompose the effects and measure the significance of income ranking on mortality rate. Finally, temporal and spatial analysis were conducted to identify associations between state level mortality inequity over time.

Paper 2 takes a similar approach to measuring inequities in under-five mortality rate in India. Data were available for two time points only, 2001 and 2012 and the measure of economic well-being used was wealth index rather than income. Health inequity between districts was measured at national level for 2001 and 2012, and the statistical dominance of inequity in 2012 versus 2001 was measured. The effects of wealth ranking and other economic and demographic characteristics at district level were decomposed. The analysis was then repeated at state level for both time points and the variation in inter-district inequities between states was measured. Finally, spatial associations between state-level inequities were measured.

Paper 3 took the results from paper 1 and measured the effects of redistributive transfers from state to county level upon mortality inequities over time. A panel model was constructed to model the effects of these transfers, along with county level social spending and several economic and demographic characteristics of states over the period 1972 to 2012.

Study aims and hypotheses

Aim 1:

Construct an innovative measure for spatial health inequalities between sub-national areas, and determine their performance in tracking changes over time in the US

- *Hypothesis 1.1: Geospatial health inequalities between US counties are statistically significant and have increased between 1972 and 2012*
- *Hypothesis 1.2: Geospatial inequality between US counties remains statistically significant after including relevant demographic, coverage and access characteristics in a multivariate analysis*

Aim 2:

Use the measures developed in Aim 1 to analyze inequality in child mortality across districts in India and assess its significance. Track how inequality has changed over time to assess how equitably mortality decline has been realized across India's districts.

- *Hypothesis 3.1: Geospatial health inequalities between Indian districts are statistically significant and are larger in states with lower mortality.*

- *Hypothesis 2.2: Geospatial inequality between districts of India remains statistically significant after including relevant demographic and economic characteristics in a multivariate analysis*
- *Hypothesis 2.3: Geospatial inequality between districts of India have increased nationally and at state level between 2001 and 2012*

Aim 3:

Use the geospatial inequality measures calculated in Aim 1 to test the responsiveness of inequality to state and county spending.

- *Hypothesis 3.1: Increasing inter-governmental state transfers to counties is associated with a reduction in the level of health inequality between US counties.*
- *Hypothesis 3.2: Increasing county level public spending on social services is associated with an increase in the level of health inequality between US counties.*

Chapter 1 References

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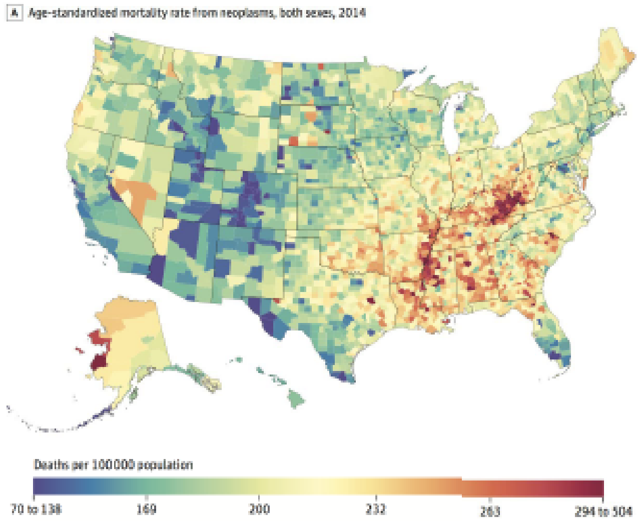
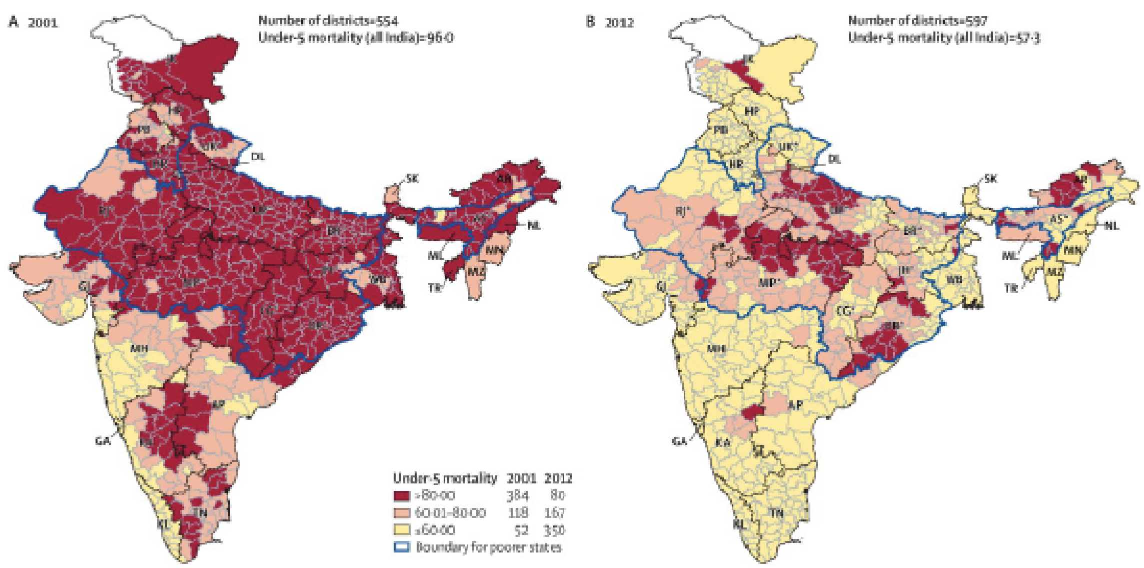
Figure 1.1: US County Mortality Rates from Neoplasms in 2014



Source: Dwyer-Lindgren et al., 2016

Figure 1.2: District Under-Five Mortality Rates in India in 2001 and 2012



Source: Ram et al., 2013

Chapter 2 (Manuscript I): Temporal and spatial patterns of geospatial mortality inequity in the US

Introduction

The academic literature on health equity in the US has focused largely upon racial or ethnic inequalities, or individual income inequalities [1, 2]. However health inequalities between counties and commuting zones have received attention recently [3, 4]. Consideration of alternative perspectives, comparing populations defined in different ways, paints a more complete picture of the complex social interactions behind health inequities [5, 6].

The existence of geospatial health inequity means health is segregated by place, based upon the economic well-being of the population in each place. The character of a community has tangible meaning in the lives of its population. The cyclical deterioration of poor cities and parts of cities, and the sustained neglect of poor rural areas illustrates the effect of living in a high or low income community. Cycles of deterioration in social determinants of health can be specific to local communities, as educational facilities and green spaces within these communities can deteriorate or flourish, depending on investments from local populations and governments. This has resulted in geospatial inequities between counties in the US, with a divergence in health behaviors, health education and healthy environments. If then those living in poorer communities experience this inequity in their daily lives there are additionally potential negative impacts for their psychological health. Given the importance of this perspective of health equity, a summary measure of such inequities would be a useful tool for national and state-level policymakers to understand their extent and design policies to reduce the real and visible disparities that exist.

This analysis proposes a new measure of mortality inequality, the Inter-County Concentration Index (ICCI), which focuses attention on geospatial health disparities rather than groups based on individual characteristics. The ICCI measures the cross-county equity of health and can be interpreted as the percentage of all the health outcomes from the richest 50% of counties must be transferred as a lump sum to the poorest 50% of households to equalize the cross-county equity of health. It presumes that a state has a social goal of making a county's health invariant to how rich or poor a county is.

The analysis will:

- Measure inter-county inequalities across the US over the time period 1972-2012
Measure the statistical significance of mortality inequality at each time period and any dominant trends over time
- Measure inter-county inequalities within each state over the same time period and investigate the level of variation and consistency between states
- Investigate temporal and spatial associations between inter-county concentration indices at state level

To test the robustness of the measure, the analysis will also compare mortality inequalities using the ICCI to two alternative measures, the Slope Index of Inequality and the Coefficient of Variation.

This research takes an innovative approach to a field that is garnering increased attention in research and practice. It complements the existing body of literature by focusing on health inequalities from a geospatial perspective, and results should be understood in the context of the work that has been done on mortality disparities in the US, some of which disaggregates racial and economic disparities by place. This perspective also highlights in particular the potential role for public health in addressing inequalities. Health departments and government at county and state level already implement interventions at geospatial scope and may find this a valuable approach to redistribute health amenities within their jurisdictions.

Background

The WHO defines health inequalities as "inequalities in health status, risk factors, or health service utilization between individuals or groups, that are unnecessary, avoidable, and unfair" [7]. Health inequity exists where there are avoidable and unjust differentials in the health status of groups or individuals [8]. Such differentials can result from social and economic inequalities including the unequal distribution of income, education, environmental risk factors and other determinants of individual and population health [9]. Culyer & Wagstaff have explored alternative definitions of equity as it relates to the equalization of resources, opportunities or outcomes, in particular equality of expenditure per capita on health, distribution of health resources according to need, equality of access to health or healthcare, and equality of health [10]. This research relies on an 'equality of health' definition and uses health outcomes, primarily mortality rates, to measure health equality. Equality of health is conditional on a respect for autonomy and a prohibition on reductions in current health [10]. Studies of mortality inequalities in the US have focused on social determinants such as race and education interactions [11], educational gradients in mortality [12] and individuals' income levels [3, 13]. Kindig argues that discourse on health inequalities in the US is almost exclusively understood as relating to racial inequalities [2]. While health outcomes such as mortality rates among minorities are deserving of specific attention, the relative size of poor white populations represents a greater health burden to society. Both burden and rates must be considered when addressing health inequity.

Geospatial and environmental approaches to mortality inequalities are less common but have emerged from several other studies. Recently, some important health inequality literature has placed geographic location at the center of the analysis: Chetty and colleagues used individual level income and deaths data to study trends and inequalities in life expectancy from age 40 [3]. One of their key findings was that the poorest populations have relatively lower mortality in wealthy areas (commuting zones) than those who live in poor areas. Currie and Schwandt grouped counties into income quantiles, rather than individuals, and found that gains in life expectancy have been generally equal across quantiles but there is interesting variation between subpopulations [4]. Murray and colleagues found significant mortality disparities between groups defined by race, county and income, although these are aggregated in such a way as to no longer represent real geographic locations [14]. Singh and Siahpush constructed an area-based deprivation measures, or Deprivation Indices, and grouped counties into deprivation deciles to find increases in absolute and relative inequalities in life expectancy between 1990 and 2000 Censuses [15, 16].

Defining a geospatial inequality measure requires the justification of a place-based population as the primary unit of analysis. Krieger defines populations as having four sets of key relations; genealogical, internal and economical, external and ecological and teleological [5]. Geographic location does not necessarily match nationality, ethnicity or ancestry of a population, however there is often a set of shared environmental and political factors attached to a location that can uniquely affect the health of its population. When considering many health outcomes social or economic factors such as income or race might take on the more dominant roles however the political and environmental setting in which a group is situated often remains significant [1]. Krieger outlines how a nation-state can meet her four criteria in its intrinsic internal and external relationships, based largely on shared government authority over economic, legal, political and social relationships within its remit [5]. This argument can be extended to sub-national geographic areas, such as states, counties and districts, although they might lack some of the legal and political distinctions of a nation-state, many of the social, economic and political considerations are the same.

Inequalities between such populations can only exist if there is a mechanism through which health is concentrated according to a socio-economic measure. This analysis assumes that households migrate to 'healthier' counties according to their ability to pay, increasing the tax base upon through which these counties can afford greater expenditures on health-improving public amenities. The theoretical model underlying this research is Tiebout sorting. The theory predicts that people self-sort based on preferences for the amenities and tax regimes attached to a given community [17, 18]. Considering health production by local government as the choice amenity, we assume that households move to maximize their utility subject to preferences and ability to pay. This results in sustained, and potentially exacerbated, health inequalities as populations are self-segregated geospatially according to their income and preference profiles.

The first part of this paper describes the inequality measure used and applies them to examine inequality between counties across the entire US and how this has changed over time. Alternative measures are calculated using the same approach to check how consistent geospatial inequities are across measures. This is followed by a state-by-state and regional analysis, demonstrating the application of this inequality measure at sub-national level and identifying where inequality has increased the most and the least. Spatial and temporal associations are then measured to identify any clustering of mortality and income within states and across state lines and any autocorrelation in our measure over time. Finally, a decomposition is performed to assess the robustness of our measure to adjustment for factors other than income that affect county mortality rates.

Methods

Data

Mortality data used in the analysis are age-adjusted rates from the National Vital Statistics System. These are taken from the compressed mortality file prepared by US DHHS, CDC, NCHS and OAE and made available through the CDC WONDER system, available from https://www.cdc.gov/nchs/data_access/cmf.htm. Numerators are calculated from death certificates and denominators from Census populations according to place of residence, including total US, Census region, Census division, State and County [19]. Mortality data is collected by state registries. All deaths are captured and denominators are from population Census estimates. Data is collected across all 3,144 counties or county equivalents in the US. The compressed mortality data, used in this analysis, included mortality and population counts from 1968 to 2012 by cause of death (according to ICD 8,9 or 10 depending on year), state, county, age, race, sex and year and the period of analysis is 1972 to 2012. Counties for which there are 20 deaths or fewer in a year are censored from that year of reporting, other than this reporting is complete and of high quality. Rates are standardized to the age structure of the US population in 2000. Life expectancies at county level are from Institute for Health Metrics and Evaluation [21] which contains estimates of county-level life expectancy from birth every five years from 1985 to 2010, available from http://www.healthdata.org/us-health/data-download. Median county income is from the Census Small Area Income and Poverty Estimates [21] and other demographic and economic variables are from the Interuniversity Consortium for Political and Social Research and Haines [22]. There were no missing county level records in demographic and income data. Details of the US Census sample sizes and data quality by year and definition are available from http://www.census.gov/acs/www/methodology/sample-size-and-data-quality/.

Conceptual Framework

A geospatial measure of health equity is used for this analysis. Previous studies of health equity tend to focus on populations defined by race, individual income or education [1, 2, 3, 8, 9, 11]. However there are spatial and political considerations that can result in Social and economic environment, disease profile, climate and environmental features of a place can have causal effects on family and individual health [23, 24]. Government and other public health actors exert influence on the health of a place through policy and resource allocation mechanisms. Studies have demonstrated that public policy and public health spending have been significant drivers of mortality decline over the past two hundred years [25,26]. Despite this, the individual measures of health inequality rely heavily upon a concept of health derived from the Grossman model of health capital [27]. This model assumes that health is individually determined, with little role for the government or the political economy of public health spending within geospatial boundaries. Our inequity measure aims to take into account the political, cultural and environmental differences between geospatially-defined populations that lead to health inequity.

The concept behind this definition is as follows. Each county has a distinct population profile that includes income and preferences for health amenities (compared with other consumption). The county defines a set of health amenities based upon the preferences of its constituents and their ability to pay taxes. Therefore, counties of the same income with higher preferences for health will have better health producing amenities, as will places of the same health preferences but higher incomes. This is what we define as health inequity, the stratification of counties by health and income. Furthermore, households faced with the choice of counties will choose the county that matches their health preferences, subject to their ability to pay the requisite taxes. For a given level of health preference, people will therefore self-sort by income in a form of Tiebout sorting. Geospatial health inequity is, in this way, self-propagating. This is described in visual form in Figure 2.1.

Statistical Analysis

The measures of mortality inequalities used in this analysis are the Concentration Index (CI) and associated Concentration Curves, the Slope Index of Inequality (SII) and the coefficient of variation. These methods are adjusted from traditional approaches by comparing geospatial populations rather than populations defined according to social or economic measures, as is more usual [28, 29]. The CI is the primary inequality measure used for this study. This index uses a measure of living standards, such as consumption or income, and a measure of health whose distribution is of interest. If the ranking of health is equivalent to socioeconomic ranking, this measure is equal to the standard Gini coefficient and the concentration curve is equivalent to the Lorenz curve [30]. Groups are ranked according to the living standards measure and plotted cumulatively on the x-axis. The health measure for each group is plotted cumulatively on the y-axis. This results in a curve emanating from the origin, with the area between the curve and a 45-degree line from the origin representing the extent of inequality between units of analysis. If everyone has the same value of the health measure regardless of their income/living standard, then the curve and 45-degree line will coincide, and inequality will be zero. This is illustrated in the sample graph in Figure 2.2.

The concentration index measuring inequality is twice the distance between the concentration curve and the diagonal. If the cumulative health measure as a function of the cumulative share of groups ranked by living standards is denoted h(s), the CI can be calculated as:

$$CI = 1 - 2\int_0^1 h(s)ds \tag{2.1}$$

This is clearly less than zero when the curve is above the 45 degree line, and is equal to zero when they coincide. The expression for the CI can be restructured as an OLS regression, as derived in Kakwani, Wagstaff and vanDoorslaer [30. If we signify r_i as the fractional rank and σ_r^2as the variance of the fractional rank, we can estimate the regression:

$$2\sigma_r^2\left(\frac{h_i}{\mu}\right) = \beta_0 + \beta_1 r_i + \varepsilon_i \tag{2.2}$$

The estimate of β_1 in this expression is the CI. Weights for group i denoted as w_i, the fractional rank must be adjusted to reflect this, so $r_i = \sum_{j=0}^{i-1} w_j + \frac{w_i}{2}$ .To include other covariates we expand equation (2) to include a range of standardizing variables directly in the regression. This results in an indirectly standardized estimate of C from the regression:

$$2\sigma_r^2\left(\frac{h_i}{\mu}\right) = \beta_0 + \beta_1 r_i + \beta_2 X_i^T + \epsilon_i \tag{2.3}$$

where X_i^T is a vector of controls and β_2 is the vector of corresponding coefficients. The effect on inequality attributable to our primary ranking variable r_i may reduce or increase as other explanatory variables are introduced to the regression. CIs are calculated with and without population weighting, however most of the results section focuses on unweighted values. This is because we are treating the county as the unit of analysis and our primary interest is in detecting the effects of place, regardless of the population of that place. State specific analyses included population weighting to provide an alternate measure of overall inequality, as well as regression adjustment for population, education and other important variables.

Statistical dominance is method of ordering used in decision theory when there are ambiguous differences between two measures [31]. Dominance in this sense is a measure of significant difference between inequality at two times or locations taking into account differences across the entire curve. This analysis tests for significant differences at 19 evenly-spaced points along the curve, implemented using the user-defined Stata programme glcurve [28]. For example, in Figure 2.3, the concentration curve of State A dominates that of State B as it is further from the line of equality at all points along the curve, assuming that these differences are found to be statistically significant. However State C concentration curve crosses over that of State A and therefore neither will be found to be statistically dominant. In some cases it will be an interesting finding to observe the extent of inequalities over subsets of the curve, for example to observe the relative size of the effects of inequality upon the poorest 10% of counties. In this example, State C has a higher proportion of mortality among the poorest states than state A but also a higher proportion of mortality among the richest states. However the test for dominance in this analysis is calculated across the entire population of counties, as the proportion of mortality among the richest counties is still a lot lower than that of the poorest counties within the state. To unequivocally say inequality has risen, it must be higher across all quantiles.

One aim of this analysis is to compare the inter-county concentration index with other measures of inequality used in previous analyses as it is a new formulation of the CI concept. Wagstaff, Paci and van Doorslaer compared the most important measures of health inequality and conclude that the CI and the Slope Index of Inequality (SII) are the only two that adequately represent socio-economic inequalities in health across the entire population [32]. The, SII is also a ranking-based index and has been widely applied in the literature [33, 34, 16]. This approach calculates this gradient in absolute terms by regressing county mortality rates on median county incomes using a weighed least squares approach. All counties are ranked by median income. For each rank, the cumulative number of cases with that rank or lower is divided by the total number of counties to get the proportion equal or lower. The mortality variable is then regressed upon this proportion and the slope of the regression line relating the county's mortality to its relative rank is the SII. It can be interpreted as the absolute effect on mortality of moving from the lowest to the highest median income level [32]. The SII analysis in this paper was implemented using the Stata user-defined program riigen which packages these computations for easy application [33].

Recent research comparing the use of various inequality measures has argued that the disadvantages of simple inequality measures may be outweighed by their straightforward interpretation and suggest measures such as standard deviation or coefficient of variation in mortality rates, absolute differences in mortality, richest-to-poorest quantile ratios or ranges [36, 37]. We have chosen coefficient of variation as our easily-understandable measure as it captures the variability between counties but standardizes by the mean level so that we can compare over time and between states. The main drawback in this measure is that it takes no account of the relative economic position of counties and so it is not directly comparable to the CI.

Results

The national level analysis indicates that inter-county mortality inequalities are statistically significant for all years and concentration curves for all but one time period are statistically significantly dominated by those of the following time period. Table 2.1 shows the range of ICCI values from 1972 to 2012, calculated with county population as a covariate and alternatively using population as a frequency weight. The largest increases are seen between 1987 and 1992, during which time inequality increased by over 7% per annum, and the only reduction was a 1% per annum fall between 1977 and 1982. Effect sizes are small, which is to be expected given the low levels of all-cause mortality. On average, ICCI increased by 3.2% per annum over the 40-year period. We use a linear transformation derived by Koolman and Van Doorslaer to make interpretation of the ICCI more intuitive [38]. The ICCI of -0.061 in 2012 means that 4.6% of mortality would have to be redistributed from high median income counties to low median income counties to achieve equality. The patterns we observe in the ICCI over time are consistent with other measures of geospatial inequity, including the Slope Index of Inequality and the Coefficient of Variation, and replacing county mortality rates with county life expectancies. These robustness checks of the measure are described in more detail in Appendix 2.1.

To disaggregate within-state variation from between-state variation we calculated the intra-cluster correlation coefficient for the national ICCI, clustering by state. This was 37%, suggesting that a substantial proportion of total variation between counties occurs within states. The state level analysis shows that each state follows its own pattern, however a general upward trend has emerged. Between 1982 and 2012 there was a general pattern of statistically significant concentration indices and upward trends, with an average annual rate of increase of over 5% per annum since 1982. Figure 2.4 illustrates the trend for each state over the period 1972 to 2012.

On average state level ICCIs have doubled since 1992 and are more than five times the levels they were in 1982. The largest increases over the entire period were found in Colorado, Kentucky and Arkansas. Arizona, Nevada, Massachusetts and New Hampshire saw significant decreases over the period. Some states containing a very small number of counties or with missing data, were excluded from further analysis, including Rhode Island, Delaware and Alaska. Alaska (AK) has missing data up to 1987 and then rises to the top of the ranking by 2012 which may distort the overall pattern.

Figure 2.6 illustrates the distribution of state level ICCIs with a choropleth map of the US in 2012. States with the highest ICCIs include California, Virginia, Kentucky, Louisiana, Colorado and South Dakota. The lowest inequality is seen in Vermont, New Hampshire, Iowa, Oregon, Montana and Texas. These differences can be better understood based on the mortality and income heterogeneity within states. Figure 2.7 highlights the counties with mortality rates in the upper half and incomes in the bottom half of the distribution, and Figure 2.8 highlights the counties with mortality in the lower half and median incomes in the upper half of the distribution. Although ICCIs take account of the entire distribution, these maps give some insight into the geospatial patterns of mortality and income. There is clear clustering of mortality and income characteristics found, both within states and across state boundaries. Southern states along the Mississippi valley are prominent in the map of unhealthy, poor counties, as is Appalachia and native American reservations. The urban Northeast, upper Midwest and West are prominent in the map of healthier, higher-income counties, with visible effects of population and urbanicity. Some low ICCI states, such as Vermont, New Hampshire and Iowa, contain counties that are uniformly in the healthier, high income half. States such as California and Colorado have lower mortality in wealthier, urban areas so the relationship between income and mortality generates high ICCIs for those states. Louisiana, Kentucky and Virginia have sections of the state at each extreme, leading to higher ICCIs, while almost all counties in Mississippi and Alabama appear in Figure 2.7 and are uniformly worse-off, generating lower ICCIs.

As some of these patterns appear regional rather than only capturing inequity within states, we extended the analysis to Census regions. At a regional level, the greatest inequity is found in the South, followed by the West. Levels are statistically significant across all regions and are of a similar order, reflecting the fact that counties at both extremes of the distribution exist in all four regions. All regions have experienced rising inequality since the mid-80s, with the largest change again between 1987 and 1992. Figure 2.5 graphs the trend in ICCIs by region and Table 2.2 lists the levels and annual increases.

A cross-sectional decomposition analysis was performed for 2012 to identify important demographic characteristics at county level that affect variation in mortality rates. A range of model specifications were tested, starting with the basic ICCI regression, which included only the median county income and county population. Independent variables were then added incrementally, including county-level measures of education, urbanicity, race and ethnicity. A range of specifications are shown in Table 2.3. Non-significant variables were not included in the final specifications. County mortality rates showed large negative associations with education and smaller negative associations with Hispanic population proportion. They showed positive associations with African American population proportion and proportion of population living in urban areas. The ICCI was robust to all specifications and remained significant at a level of 0.01 throughout. Specification 5 explained 42.4% of variation in all-cause mortality rate and adjusted ICCI was -0.042, meaning 3.1% of mortality would have to be redistributed from the poorest half to the richest half of counties to achieve equality.

Moran's I tests were conducted to detect any spatial correlation between ICCIs of adjacent states. No correlation was detected, and a correlogram of lagged state association can be seen in Figure 2.9, suggesting that there is no spillover in mortality inequality between adjacent states. ICCIs by state were regressed against year to investigate temporal associations. Figure 2.10 compares the lagged residuals of regressing ICCI against year. There appears to be some association in recent years at short lags and decreasing association over time. This pattern is reflected in Table 2.3, which shows mean autocorrelation across each 5-year lag. The Woolridge test for autocorrelation across multiple panels finds significant first-order autocorrelation in the data, so any further analysis of this measure will need to allow for serial correlation [39].

Discussion

These results demonstrate that inter-county mortality inequalities are significant and have been increasing at national level over the period 1972 to 2012. This is consistent with other inequality literature, which has shown differentials in the income and deprivation levels between areas are associated with mortality inequality [3, 16] and inequality has deteriorated in recent years [40, 41, 42]. In addition to the national trend in inequality, interesting variation by state and by region has emerged from the analysis. We find small effect sizes as mortality in the US is generally low when compared internationally. However they are statistically significant and each concentration curve dominates previous curves demonstrating that this measure has relevance and interesting temporal variability. State-by-state results indicate that it is worthwhile to break down the analysis by state as the intra-state variation may be most interesting to state- and county-level policymakers and researchers. ICCIs remain significant in the decomposition at state level after adjusting for other significant factors including education and urbanicity.

The geospatial distribution of county mortality and mortality inequities displays clustering both within and across states lines. This is paralleled in results from a recent paper from Dwyer-Lindgren and colleagues, who analyzed trends in county mortality rates by cause of death between 1980 and 2014 [43]. Deaths from neoplasms and cardiovascular disease are consistent with the state-level patterns seen in Figures 2.7 and 2.8, with inequities in California and Colorado driven by healthy counties, inequities in Louisiana and Alaska. Equities in Mississippi and West Virginia driven by consistently poor, unhealthy counties across the entire states. Both Dakotas have extremely poor and high mortality individual counties that largely correspond to Native American reservations. Appalachian counties in Virginia and Kentucky drive large ICCIs in those states [43].

The interpretation of this measure is quite different to previous applications of the concentration index at the individual level. The usual CI measure is based on individuals' circumstances regardless of where they live and is largely a theoretical construct. In contrast, a unique feature of the inter-county CI is that it characterizes some areas as 'poor and sick' and some as 'rich and healthy'. It is not simply a theoretical construct, since these differences, if they exist, are visible and tangible within the communities and environments in which people live. It may be perceived as more difficult to escape a place with a prevailing environment of poor health than a poor individual surrounded by healthy neighbours. Negative psychological effects of being exposed to areas with higher living standards while living in poor areas have been found [44, 45, 46].

Local health amenities may be particularly important when considering mortality inequities. One of the main findings in a recent large study concerns poor individuals living in higher-income areas, particularly cities such as New York and San Francisco [3]. This study groups individuals based on their income and the commuting zone in which they live and investigates life expectancy inequalities from age 40 between 2001 and 2014. Large and growing inequalities were detected, with substantial variation by commuting zone. This variation is largely driven by place-based differences in life expectancies among low-income populations. A strong association is found between life expectancy of poor populations in areas that have better health behaviors such as lower smoking rates and higher exercise rates. Weak associations found with healthcare access and income inequality. They also find small associations with air pollution and access to good food, which are relevant to geospatial differentials.

These results suggest that either the health choices faced by poor individuals in rich and healthy counties are different than those faced by poor individuals in poor and unhealthy counties, or the poor people in these counties may be different. Unhealthy behaviors and health choices of those in poverty may be rational in some contexts. The theory of rational addiction suggests that smoking or alcohol abuse may be a rational behavior given that loss of future income represents a lower opportunity cost [47]. The poor may also be more likely to engage in quasi-hyperbolic discounting and therefore may be less likely to choose future benefits of healthy living over immediate costs [48, 49]. The Grossman model places a greater opportunity cost of investing time in a healthy behavior such as exercise for the rich, however at lower incomes the opportunity cost may be the loss of a job and not based on hourly income [27]. The existence of green spaces in a city may make the opportunity cost of exercise and outdoor activity lower for everyone, with greater benefits to those who are less likely to exercise otherwise. State or county policies regarding cigarette taxes, nutritional information availability at fast-food restaurants, child nutrition subsidies may also change the cost of engaging in healthy or unhealthy behaviors in a given jurisdiction. Social norms in an area can also play an important role [50]. Therefore even if unhealthy choices are rational in some contexts, the logic may be different based on the local environment, culture and opportunity costs.

It would also be consistent with these results if the poor population of healthy counties is different to the poor population elsewhere. Returning to Tiebout sorting, people choose to live in a county with a given profile of public health amenities based upon their preferences for health and the cost, subject to their income. The relative cost of moving to a healthy place is higher for poor than for the rich. For a given cost of living in a healthy county, those that move there have a stronger preference for health than those that remain. This self-selection into healthy areas by poor people with a strong preference for health amenities means that poor people that move to those areas are fundamentally different to rich people in those areas and different to poor people who live in lower income, higher mortality counties.

Regardless of the clear variability that emerges from this analysis, it is not entirely clear whether geospatial equity is important to policymakers. As is clear from Figures 2.7 and 2.8, addressing health inequity may be in conflict with aims of addressing absolute levels of poverty and mortality. Inequity in California is driven by extremely low mortality and high income counties on the Southern coast versus moderate indicators in the north and east, whereas relatively low ICCIs in Mississippi and Alabama are driven by uniformly poor indicators across counties. A national level policymaker may feel ethically obliged to address the higher mortality in Mississippi than the inequity in California. However, the systematic and sustained characteristics of geospatial health inequities represent a challenge distinct from overall mortality reduction.

Kindig argued that the focus on racial inequities in the study of health inequity hinders efforts toward their reduction [2]. Just as sustained, systematic race-based inequities have their roots in historic and social injustices, geospatial inequities can be unjust in sustained and systematic ways. In places with lower income levels, hence lower individual investments in health, the local tax-base is smaller. This leaves fewer resources for public health such as investments in local health amenities, education and environment, potentially compounding the negative effects on social determinants of health and widening health gaps between poor and rich places [2, 9]. If populations of wealthier places tend to live longer, they have more aggregate years during which to realize social benefits such as health care in older years and social security benefits. This represents fiscal inequity within a jurisdiction and could be considered fundamentally unfair to shorter-lived populations such as the Scots in Britain and the Walloons in Belgium [51, 52, 53]. Finally, the association of income-related inequality by place leads to a heterogeneous set of health/wealth county profiles [3, 54]. The frequent exposure of people living in 'poor-sick' places to those more advantaged can lead to a psychological health burden and toxic stress over the life-course [55, 56, 57]. State policymakers require a geospatial measure to address these cycles of injustice between their constituent counties.

The policy prescriptions to address high individual and high geospatial concentration of mortality, as measured by ICCI, may differ. A high CI based upon individuals' incomes can be addressed through individual targeting, for example means-tested interventions such as Medicaid or food stamps. In contrast, public health departments and other local government have a geospatial remit. Local amenities, from policing to garbage-collection to pollution and green spaces have non-excludable benefits that can be made available to a geospatially-based population. In this regard, our results of significant and growing geospatial mortality inequality suggest a greater emphasis on public health solutions.

Limitations

A limitation of this analysis is the use of total age-adjusted mortality as the health measure of interest. Firstly, this is based on an age-standardized population and does not account for the age structure of specific counties. Our checks for consistency with life expectancies strengthen the analysis, however the data was only available at county level at four time points from 1995 to 2010. Secondly, the aggregation across all age groups may disguise some important differences between trends in adults and those among children. Currie and colleagues found that grouping counties based on their poverty rates, life expectancy gains have been distributed equally between rich groups and poor groups of counties [4]. They look at life expectancy from birth and conclude that divergences after age 40 have led to other studies' conclusions that life expectancy inequality is increasing. They report that analyzing age specific mortality rates on the same basis reveals that mortality of adults aged 50 and over has decreased more in richer groups of counties and mortality of children has improved more quickly in poorer groups of counties, so that childhood mortality is becoming more equal. They predict that due to life-course trajectories of health [58] that this should lead to reductions in inequality as these children age. This argument does not, however, explore the differences between factors related to mortality among children and those related to adult mortality, so the assumption that health equity will be retained with age is a strong one. In addition, by grouping counties based on poverty level without regard to geospatial location, they ignore spatial associations due to geographic proximity or the health policies and amenities specific to a given state.

Data at an individual level were not available to link specific health outcomes to specific characteristics. The use of aggregate demographic data including the racial and income composition of a county may be subject to bias, particularly over a multi-year panel. Migration between counties can lead to changing population structure in terms of age, race and other important determinants and can make interpretation of mortality inequalities difficult or misleading [59].

Further work is needed to investigate changes in geospatial mortality inequalities over time, and whether particular policies at state or county level have had an impact on inequality between counties at state and regional level. All-cause mortality is not a particularly sensitive indicator, so application of this method to other health outcomes would provide valuable additional perspectives, for example obesity rates, smoking prevalence and other behavioural indicators may allow state-level policymakers to redistribute resources and target interventions at a geospatial level, making use of local health departments and other agencies with a geographic scope.

Conclusions

This analysis has demonstrated that geospatial measures of mortality inequality between counties in the US are significant at national and state level and have been increasing between 1972 and 2012. These results are robust across measures of inequity and remain statistically significant after allowing for other important determinants of mortality at county level. Results display significant variation by state and clustering of high-mortality, low-income counties occurs both within states and across state lines. Such measures may be useful in testing the effects of various policies upon inequality as well as informing state level policymakers about the health inequalities that exist within their constituency. Adding a geospatial perspective to the literature of individual income and race-based inequities adds a new dimension to the complex social interactions behind overall health inequities.

Chapter 2 References

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Table 2.1: Inter-County Concentration Index (ICCI) and annual change for the US from 1972 to 2012

	1972	1977	1982	1987	1992	1997	2002	2007	2012	Average annual increase
(1) ICCI with population as covariate	-0.0176*** [0.00190]	-0.0185*** [0.00162]	-0.0176*** [0.00156]	-0.0224*** [0.00165]	-0.0315*** [0.00170]	-0.0412*** [0.00197]	-0.0456*** [0.00175]	-0.0581*** [0.00177]	-0.0609*** [0.00176]	3.2%
(2) ICCI with population weightings	-0.0172*** [0.00381]	-0.0161*** [0.00319]	-0.0139*** [0.00258]	-0.0184*** [0.00252]	-0.0277*** [0.00260]	-0.0383*** [0.00253]	-0.0459*** [0.00293]	-0.0582*** [0.00260]	-0.0661*** [0.00259]	3.4%
Statistically dominates previous measure		Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	
Number of counties	3008	2990	3031	3028	3044	3055	3057	3044	3043	
Average annual increase in ICCI		1.0%	-1.0%	4.9%	7.1%	5.5%	2.1%	5.0%	0.9%	

Table 2.2: Inter-county Concentration Index by region 1972-2012

Census Region	1972	1977	1982	1987	1992	1997	2002	2007	2012	Average annual increase in ICCI
Northeast	-0.017	-0.012	-0.011	-0.013	-0.018	-0.022	-0.029	-0.031	-0.042	2.3%
Midwest	-0.007	-0.005	-0.005	-0.007	-0.018	-0.025	-0.022	-0.039	-0.041	4.5%
South	-0.009	-0.01	-0.012	-0.017	-0.022	-0.031	-0.033	-0.042	-0.049	4.3%
West	-0.011	-0.009	-0.008	-0.007	-0.02	-0.026	-0.034	-0.04	-0.046	3.6%
Average increase in ICCI		-3.8%	-0.1%	3.7%	14.0%	5.8%	2.5%	5.4%	3.3%	

Table 2.3: Adjustment of ICCI for county-level demographic factors affecting mortality

County level all-cause Mortality Rate regressed on:	**Model Specifications**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Inter-County Concentration Index	-0.0609*** [0.00176]	-0.0432*** [0.00231]	-0.0358*** [0.00244]	-0.0415*** [0.00245]	-0.0418*** [0.00242]
Population of county	-2.70e-09*** [7.83e-10]	1.55e-09 [1.57e-09]	-2.13e-09 [4.45e-09]	-3.96e-09 [3.39e-09]	8.87e-10 [1.02e-09]
Proportion of population with a bachelor's degree or more education		-0.0897*** [0.00671]	-0.0982*** [0.00659]	-0.109*** [0.00684]	-0.110*** [0.00676]
Proportion of the population living in urban areas				0.0122*** [0.00171]	0.0122*** [0.00171]
Proportion of population with income below the poverty line			1.18e-08 [3.27e-08]	3.52e-08 [2.44e-08]	
Proportion of population that is African American			0.0369*** [0.00326]	0.0262*** [0.00327]	0.0264*** [0.00327]
Proportion of population that is Hispanic				-0.0414*** [0.00417]	-0.0413*** [0.00416]
Number of counties	3,043	3,043	3,043	3,043	3,043
R^2	0.331	0.364	0.393	0.424	0.424

Table 2.4: Autocorrelation function of state ICCIs

Lag	**Mean autocorrelation**
1	0.6747
2	0.5538
3	0.4663
4	0.4158
5	0.2946
6	0.2809
7	0.2182
8	0.0847

Figure 2.1: Conceptual Framework of the Cycle of Geospatial Health Inequity

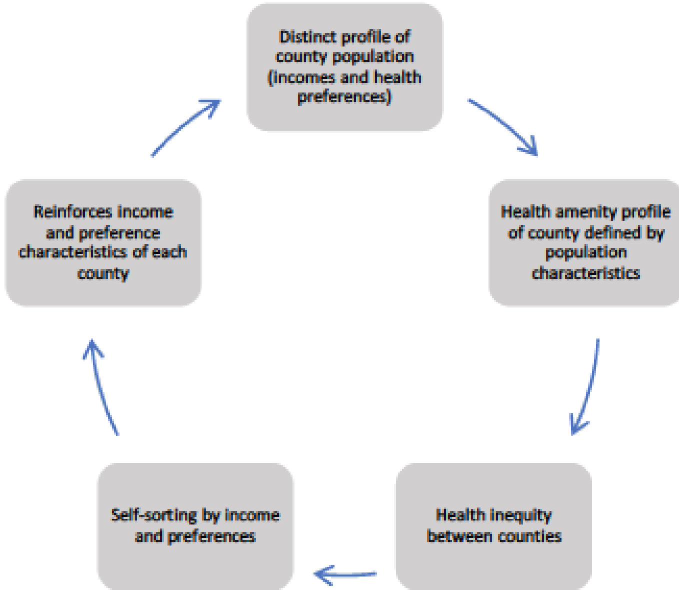


Figure 2.2: Sample inter-county mortality concentration curve

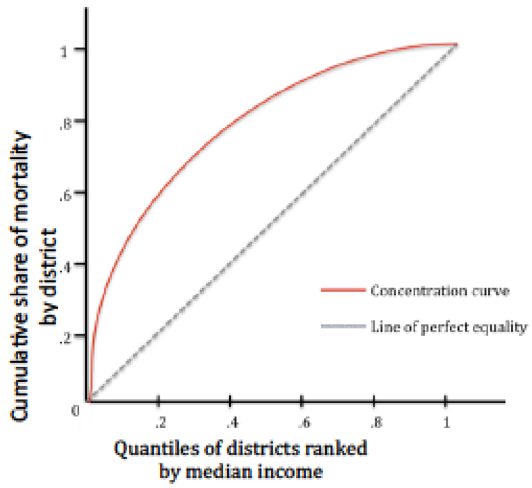


Figure 2.3: Statistically significant dominance of concentration curves

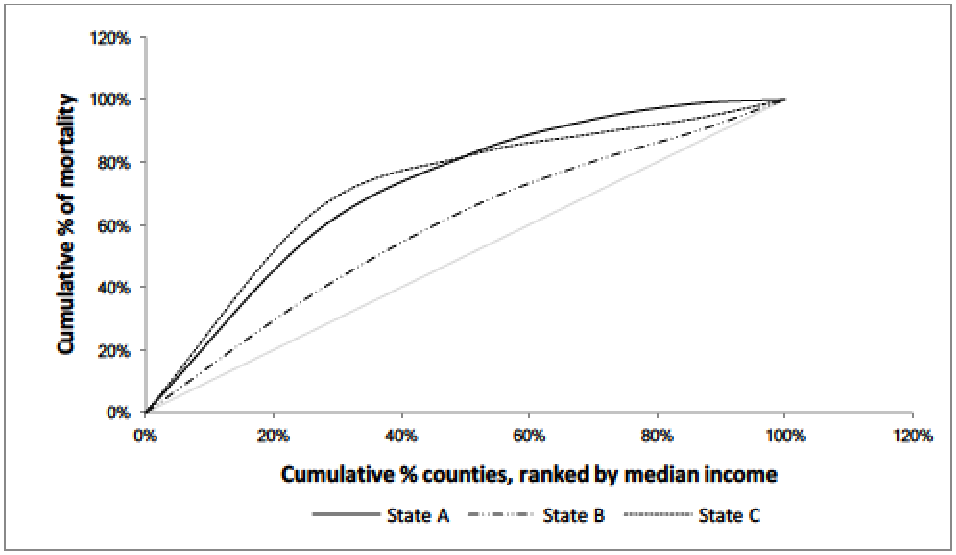


Figure 2.4: Trend in Inter-County Concentration Index, US total and by state, 1972-2012

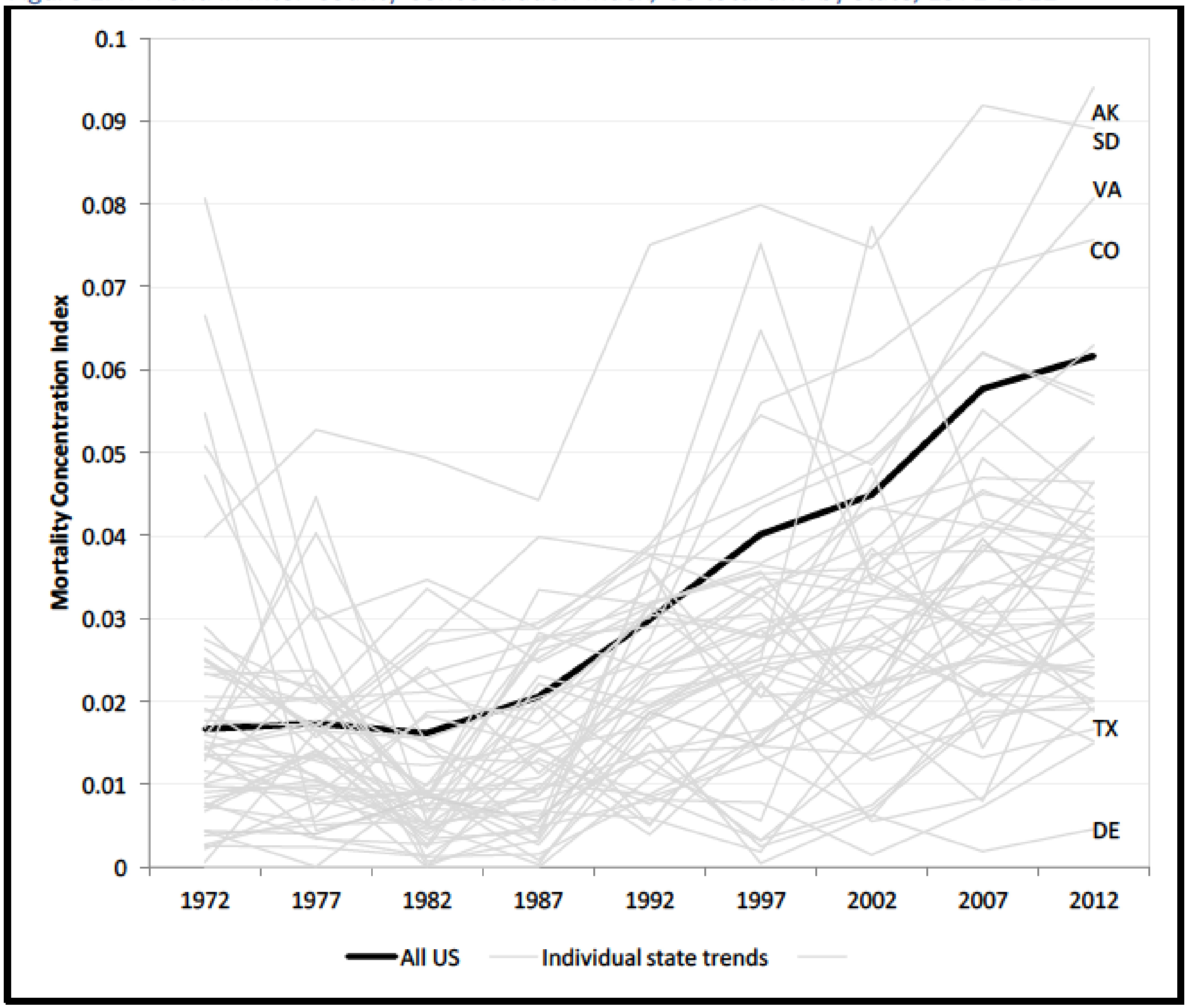


Figure 2.5: Trend in Inter-County Concentration Indices by region 1972-2012

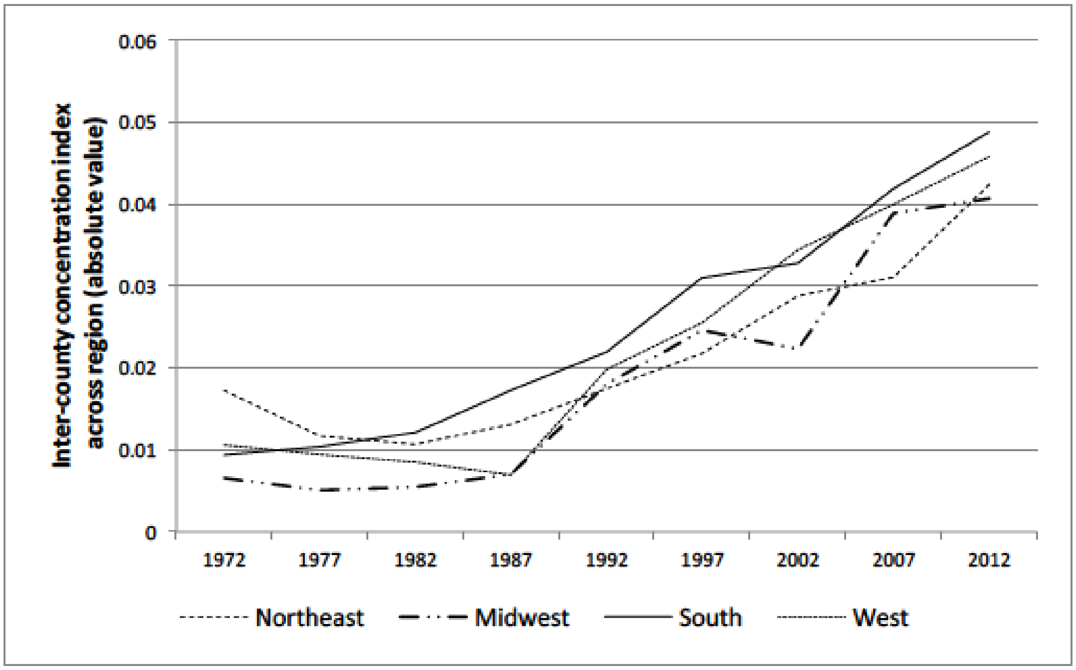


Figure 2.6: County Level Concentration Index by US state, 2012

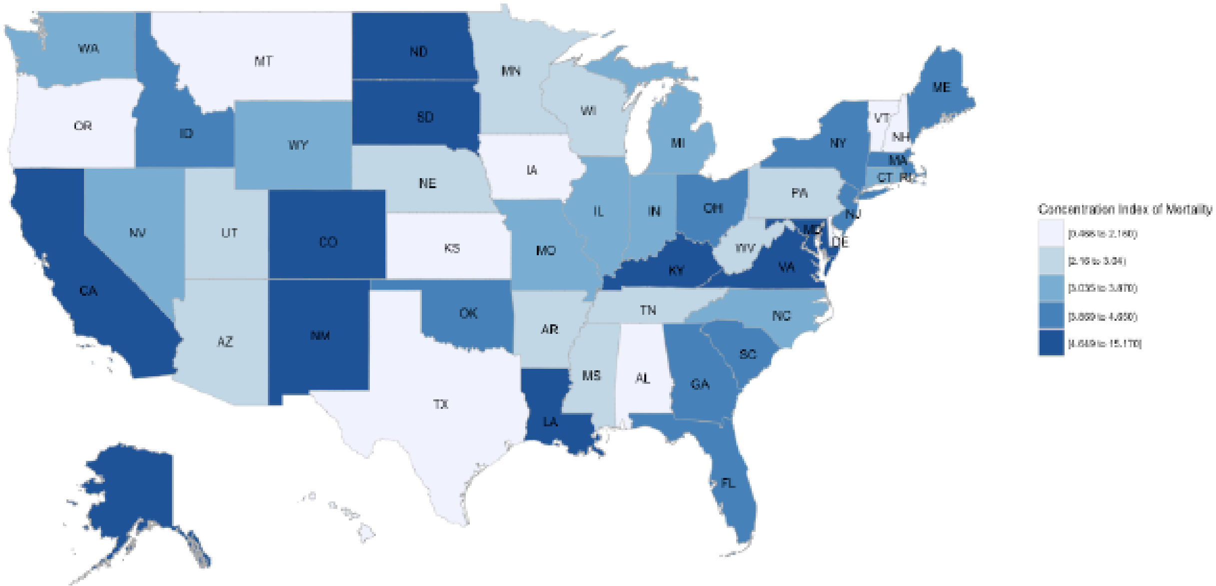


Figure 2.7: Map of the counties with above median mortality and below median income in 2012

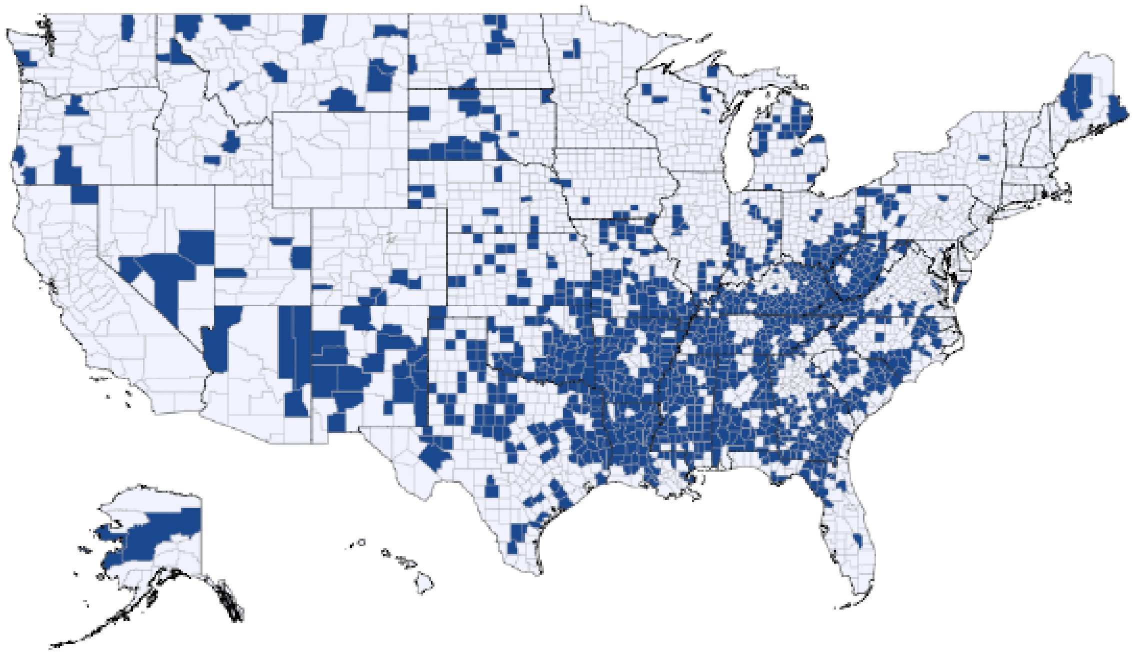


Figure 2.8: Map of the counties with below median mortality and above median income in 2012

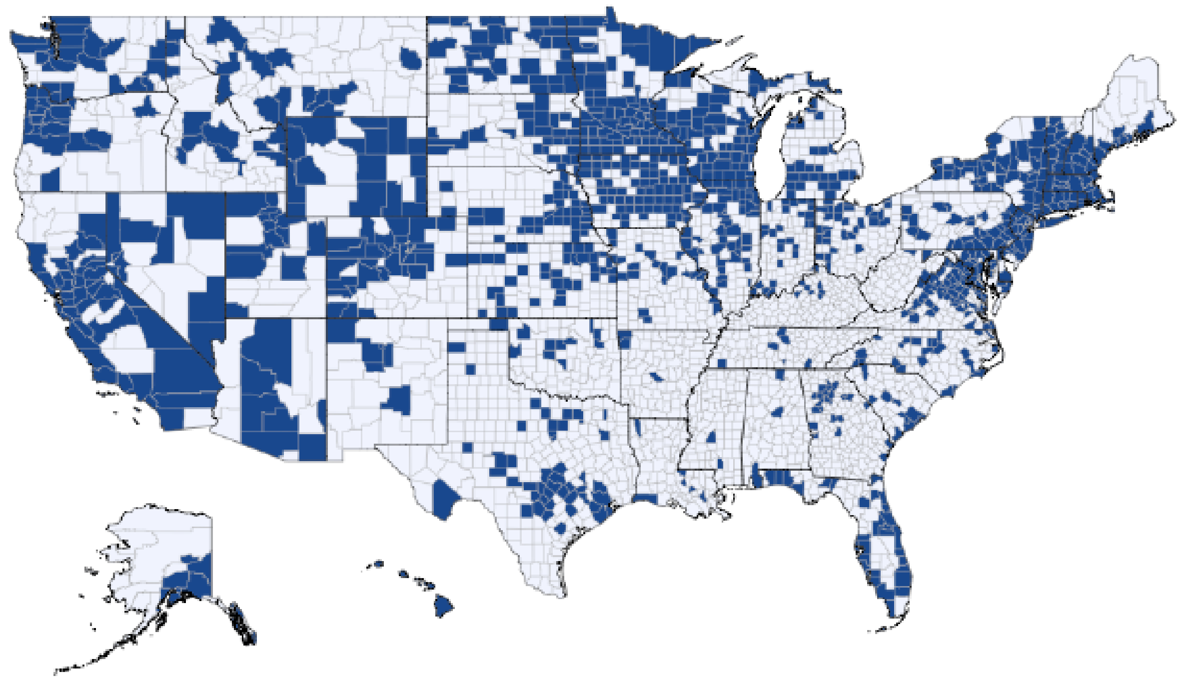
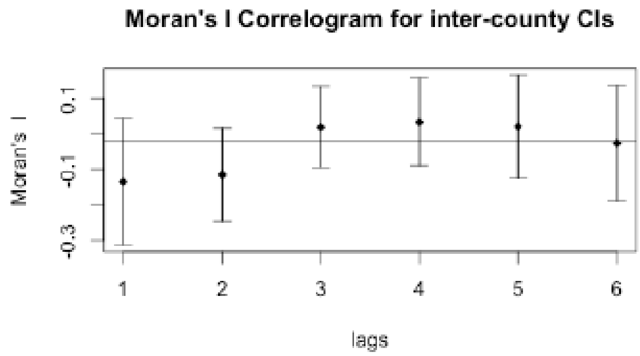
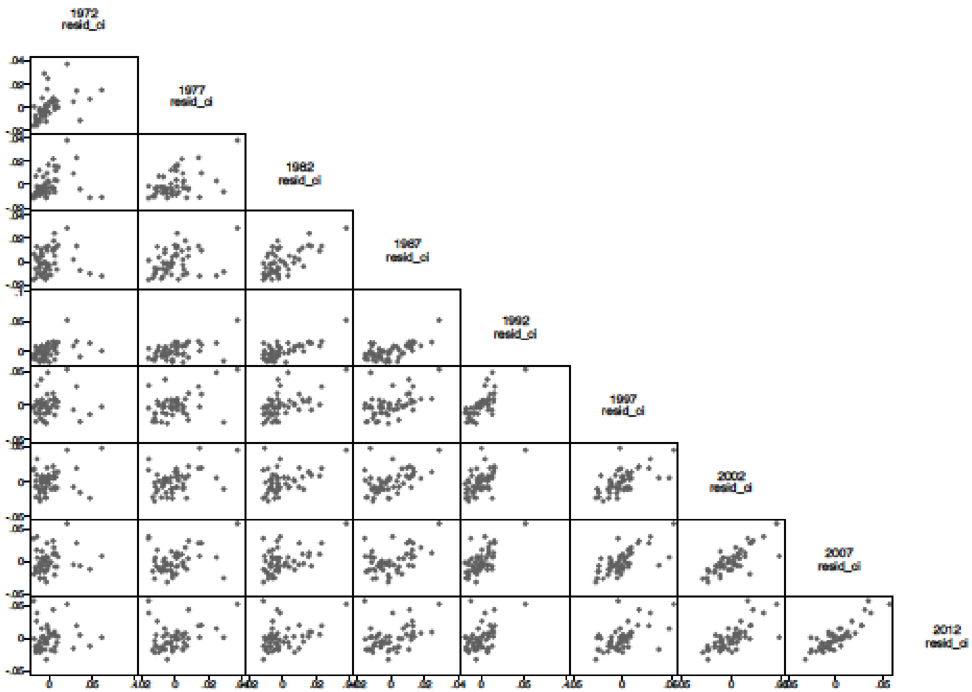


Figure 2.9: Correlogram and significance tests for Inter-County Concentration Indices by state in 2012



	Moran's I statistic	Std Dev	p-value	Expectation	Sample Variance
Randomisation (B)	-0.1329	-1.256	0.895	-0.0213	0.0079
Monte Carlo	-0.1329		0.893		
Randomisation (W)	-0.1436	-1.293	0.902	-0.0213	0.0089

Figure 2.10: Scatterplots of lagged residuals regressing ICCIs against time



Chapter 3 (Manuscript 2): Geospatial Inequity in Under-Five Mortality Rates in India

Introduction

Health equity and the existence of systematic health inequalities have been the subject of increased academic and policymaking attention in public health. The Sustainable Development Goals, recent World Health Reports and the US government's Healthy People 2020 all draw particular attention to addressing health inequalities among their priorities and aims [1, 2, 3]. The literature of health inequity in developing countries has been growing [4 - 8] as well as in OECD countries [9 – 11]. Most studies compare health outcomes, status or healthcare access between groups of individuals classified according to one or more individual economic, racial or social characteristic. This analysis proposes a new geospatial index of mortality inequality, the Inter-District Concentration Index (IDCI), and applies it to child mortality in India. The IDCI measures geospatial health disparities rather than groups based on individual social or economic characteristics. India has more under-five deaths every year than any other country with substantial variation at sub-national level [12, 13]. The IDCI measures the cross-district equity of health, ranking districts by a measure of wealth. It measures the proportion of health outcomes that must be transferred from the richest 50% of districts to the poorest 50% of districts to equalize the cross-district equity of health. This presumes that the country and state have the social goal of making a district's health invariant to how rich or poor a district it is.

Geospatial inequity has particular relevance in our lives due to the tangible nature of one's social and physical environment. If health and mortality are segregated by place then those living in poorer communities experience these contrasts in their daily lives, with negative impacts for psychological health as well as the potential for cycles of deterioration of social determinants of health within their communities [14, 15, 16]. Health equity is a multi-dimensional concept with implications for poverty reduction and social justice [17]. Such a measure of geospatial inequity provides a useful perspective for national and state-level policymakers to understand such inequalities and design policies to reduce the real and visible disparities that exist.

The analysis will:

- Measure inter-district under-five mortality rate inequalities across India in 2001 and 2012. Measure the statistical significance of mortality inequality for each time period and test for dominance between concentration curves over time
- Decompose the effects of demographic and social indicators at district level upon inequality
- Measure inter-district inequalities within states over the same time period and investigate the level of variation and consistency between states
- Investigate spatial associations between inter-district concentration indices at state level

This research takes an innovative approach to a field that is garnering increased attention in research and practice. It complements the existing body of health equity literature in India and globally by focusing on inequity from a geospatial perspective. Results are relevant for government at district and state level which already implement interventions at geospatial scope and may find this a valuable approach to redistribute public health and healthcare resources within their jurisdictions.

Background

One of the most influential factors affecting an individual's health is the place in which they live. 133 children of every 1,000 born in Rayagada district of Orissa state in India die by their fifth birthday, while in Puri district of the same state the rate is 48, almost two-thirds lower. In Kannur district of Kerala, rates close to richer countries have been achieved (8.8 per 1,000 live births) [13]. These disparities suggest that there are characteristics of these districts that affect the health of their populations. When measuring population health, it is therefore a useful perspective to define populations based on geospatial parameters. The association between health outcomes and the economic, social or demographic characteristics of the country they inhabit has been studied, notably in the Preston curve, which ranked national mortality rates against national GDP however the inequities we observe at subnational level fall within the jurisdiction of national and state policymakers and be more amenable to policy interventions [18].

Krieger defines populations as having four sets of key relations; genealogical, internal and economical, external and ecological and teleological [19]. Geographic location does not necessarily match nationality, ethnicity or ancestry of a population, however there is often a set of shared environmental and political factors attached to a location that can uniquely affect the health of its population. When considering many health outcomes social or economic factors such as income or race might take on the more dominant roles, however the political and environmental setting in which a group is situated often remains significant [20]. Krieger outlines how a nation-state can meet her four criteria in its intrinsic internal and external relationships, based largely on shared government authority over economic, legal, political and social relationships within its remit [19]. This argument can be extended to sub-national geographic areas, such as states and districts, although they might lack some of the legal and political distinctions of a nation-state, many of the social, economic and political considerations are the same. In India, studies have identified significant inequities between populations defined by social variables such as tribal, religious or caste-based definitions, as well as economic and geospatial definitions [21, 22, 23].

The lowest level of government administration in India is the Gram Parishad (village level), above that is the Tehsil Parishad (Block level), Zila Parishad (Disrict level). The Zill or District level in India is the lowest level of governance structure for which survey data on health indicators is available. While sub-district bodies have distinct roles in development planning, the district level has responsibility for such public health policies as spending on sanitation, health information and preventive healthcare. Although there are many historic and socio-economic factors that affect the relative health of these district populations, there are distinct policy and environmental characteristics attached to districts and significant health inequalities at this level have been identified [23]. State level health spending, defined broadly to include rural and urban public health services, medical education, training and research, general administration, water supply and sanitation, and family welfare, has been demonstrated to have a significant effect on infant mortality rates [24].

Faced with the choice between districts with varying public health characteristics, individuals and households may choose a district to live in based upon the cost and their preferences for public health amenities, subject to their ability to pay. There is some evidence that migration between states is low in India however there is little data on migration at district level [25, 26]. Inequalities in U5MR between districts that reflect their relative household wealth would be consistent with such self-sorting. Alternatively, health inequalities may be related to the distribution of healthcare and public health resources and the capture of health benefits by wealthier districts whose populations are better able to take advantage of them [27]. The tension between efficiency and equity in the realization of mortality improvements is discussed later in the analysis.

This leads us to the definition of the concept of equity and what is thought of as 'health inequity' as well as whether such subjective definitions should be interesting to researchers and policymakers. The WHO defines health inequalities as "inequalities in health status, risk factors, or health service utilization between individuals or groups, that are unnecessary, avoidable, and unfair" [28]. Health inequity exists where there are avoidable and unjust differentials in the health status of groups or individuals [1]. Such differentials can result from social and economic inequalities including the unequal distribution of income, education, environmental risk factors and other determinants of individual and population health [29]. Health systems consistently provide greater volume and quantity of services to the wealthy than to the poor and this compounds existing health inequity [30]. Culyer & Wagstaff have explored alternative definitions of equity as it relates to the equalization of resources, opportunities or outcomes, in particular equality of expenditure per capita on health, distribution of health resources according to need, equality of access to health or healthcare, and equality of health [31]. This research relies on an 'equality of health' definition and uses health outcomes, primarily mortality rates, to measure health equality. Equality of health is conditional on a respect for autonomy and a prohibition on reductions in current health [31]. The equality of health is the definition adopted in this analysis, with under-five mortality rate as the outcome of interest.

India accounts for 21% of all under-five deaths globally, with a U5MR of 53 per 1,000 live births in 2013 [32]. This has declined from 126 per 1,000 live births in 1990, an annual reduction rate of 3.8%. A recent study demonstrates significant differences in under-five mortality rate by district, which are broadly consistent with income differentials between regions [13]. Although rates have improved in almost all districts, this has not occurred uniformly across the country and there is clear inequality within some states and across state borders. A UNICEF study with data from the National Family Health Surveys shows that most U5MR inequality at the individual level exists in states with the highest absolute levels of mortality irrespective of the level of economic development. While there is some evidence of inequality decline overall, the direction in the trends of inequality vary by state and the analysis does not take into account the relative wealth of districts [33].

This analysis builds on the existing literature and uses the concentration index between district populations to measure inequality at two time points. It finds that under-5 mortality inequalities are statistically significant and have grown since the start of the 21st century. Other characteristics of a district such as mother's education and urbanicity also contribute to U5MR disparities between district populations, clear from the decomposition analysis. In addition, a state-by-state analysis of inter-district inequality shows considerable variation between states, with notably larger within-state inequalities in states with higher overall U5MR. This paper builds on existing study of mortality inequalities in India and contributes several unique features to strengthen the literature. Firstly, the majority of literature concerning U5MR in India is at national, regional and state level, for example the National Family Health Surveys, the Million Death Study work on causes of child deaths [34, 35] the health gains realized in Kerala without commensurate economic development [36, 37]. There has been limited study of cross-district disparities, so this approach brings an important perspective for policymakers and researchers. Secondly, construction of an inter-district concentration index at national and state level brings an innovative perspective to the study of child mortality as it highlights the differences in challenges faced between each state. As global and national goals grow to incorporate indicators of health equity and sub-national heterogeneity, such summary measures may prove valuable in identifying characteristics and policies that encourage health equity. Finally, the period of analysis was one of significant progress towards MDG-4 in India. This analysis brings into focus the trade-off between efficiency and equity in the choices faced by policymakers driven by such aggregate goals.

Methods

Data

There are no direct estimates of district level Under-Five Mortality Rates (U5MR) from survey data for all of India. The UN Population Division produces national level estimates, and the Sample Registration Survey conducted by the India Census Bureau produces state level estimates. Summary Birth History (SBH) data is collected through the District Level Household and Facility Surveys and these are the only estimates available that are significant at district level. Indirect estimates of under-5 mortality rate by district in 2012 and 2001 were calculated by Ram and colleagues. They estimated death totals at district level using the Brass method and summary birth histories from District Level Household and Facility Surveys (DLHS-2 and 3) along with UN model life tables for south Asia. State level estimates of under-five deaths were calculated the India Sample Registration Survey (SRS), adjusted for consistency with national UN mortality estimates [13]. The Annual Health Survey (AHS) of the India Census contains direct estimates of under-5 and infant mortality rates based on life tables from full birth histories (FBH). These are available at district level for 284 districts in 9 states, namely Bihar, Jharkhand, Odisha, Rajasthan, Madhya Pradesh, Chhattisgarh, Uttar Pradesh, Uttarakhand and Assam. 72% of under-5 deaths and 50% of India's population are within these states. Mortality estimates are calculated directly using life tables methods based on full birth histories collected in these states.

Demographic and economic data were from the District Level Household and Facility Surveys, DLHS-2 (2002-04) and DLHS-3 (2007-08). These surveys have been carried out in India over 4 waves from 1998 to 2013 by the International Institute for Population Sciences (IIPS), Mumbai. These are representative at district level and contain demographic characteristics as well as individual and household level behaviors and outcomes. DLHS-4 (2011-12) was not available for the 9 states that contribute more than

50% of child deaths and was not used for the primary analysis, although inequalities based on data from DLHS-4 were used as a consistency check in the Appendix. The key predictor for this analysis is an asset-score index of economic well-being at household level. Households indices are used to produce a median for each district based on sample weights. Also included are indicators of education, occupation, health status, use of and access to health care, and a partial birth history among other relevant characteristics. It is important to note that the geographic definitions of districts, and the total numbers of districts have changed over the time period as districts have been broken up, combined and have changed names. There were 593 districts in India in the 2001 Census and 640 in the 2011 Census [26, 38]. Renamed districts were matched between the two periods and analyses were carried out both based upon the common districts in all time periods and cross-sectionally for each time period.

Individual asset scores are calculated at household level in DLHS-3 as an index calculated as a weighted summary measure of household assets, including years of education of the head of household, the number of bedrooms, whether or not the house has electricity among other assets. An index was constructed for DLHS-2 from survey questions regarding individual assets. Most of the assets are binary, for example either the household has a mobile phone or not, and some ordinal, for example number of bedrooms and education level of household head. These were weighted based on the asset weightings derived by Bassani and colleagues [35], which used principal components analysis to assign coefficients to each asset. Median wealth indices for each district were calculated at each time period, based on household indices and sample weights to assign district level values.

To determine whether the median district wealth index is the best choice of economic measure for the district, robustness checks were carried out, comparing the median with the weighted and unweighted mean wealth index based on their relationship with district U5MR at each time period. These robustness checks are described in more detail in the appendix "Testing district wealth measure for robustness".

Mortality rates by district were merged to the closest year of economic and demographic indicators available. Mortality by district from the 2001 Census was merged with characteristics from the 2001-02 DLHS-2 data and mortality by district from 2012 [13] was merged with characteristics from 2007-08 DLHS-3 data. Implications of the mismatching of time periods are discussed later in the paper.

Conceptual Framework

The primary measure for health inequity used in this analysis is the concentration index and concentration curve. This has been used widely in the literature on health equity, however this application calculates a geospatial version of these measures defining districts of India as the unit of analysis rather than defining populations of individuals or household according to social or economic measures, as is more usual [39, 5]. This geospatial approach places emphasis upon the health characteristics and public health amenities attached to a distinct place. Geographic and political characteristics of a place have been included in child health frameworks in the literature, including climate and environmental features, disease profile and local economic and social factors as having causal effects on the health of the local population [40, 41]. Studies of historic mortality improvements have attributed significant effects to public health interventions defined over geographically and politically defined populations [42, 43]. Extensions to the Grossman model of health capital have been developed to allow for environmental and policy influences on health, including the effects of public provision of health amenities and exogenous environmental factors [44, 45, 46]. Health inequalities between geospatial populations can only exist if there is a mechanism through which health is concentrated according to a socio-economic measure.

There is some evidence to support the concept that increasing the resources available to a local government can improve the health of children within its constituent population. Afsaw and colleagues found that fiscal decentralization in India was associated with improved Infant Mortality Rates (IMR) in rural areas [47]. Bhalotra found that public sector spending at state level had a significant effect on state IMR [24]. Since the resources available to a district government are partially dependent on the tax base in their district, a wealthier district could theoretically spend more on health amenities and improve public health resulting in better health outcomes in wealthy districts compared with poorer ones. Secondly, private sector healthcare has an incentive to provide greater access in wealthy districts. This is particularly important when health care professionals are scarce and quality of services is variable. In India, there is substantial evidence of the migration of health care workers from poor, rural districts and slums resulting in fewer and less qualified health workers in these areas [48, 49]. Increased access to quality health services in wealthy areas may compound the geospatial inequities between rich and poor districts. Finally, although inter-district migration is not captured by Census it might play a role in acceleration of this inequity. If we assume that, on the margin, households migrate to 'healthier' counties according to their ability to pay, increasing the tax base upon through which these counties can afford greater expenditures on health-improving public amenities. This argument is based upon the economic concept of Tiebout sorting which predicts that individuals choose their communities based upon local taxes and local public amenities [50]. Considering health production by local government as the characteristic of a district that households choose, we assume that they move to maximize their utility subject to preferences and ability to pay. Assuming a degree of homogeneity in preferences for health, this predicts stratification by income, with a positive association between economic well-being and health. These factors results in sustained, and potentially exacerbated, health inequalities as populations are self-segregated geospatially according to their income and preference profiles.

Statistical Analysis

This geospatial concentration index, the Inter-District Concentration Index (IDCI) is constructed in a similar way to other group-based concentration indices as described in Kakwani and colleagues [39, 51]. This measure is similar to the standard Gini coefficient and the concentration curve is similar to the Lorenz curve with the difference that the ranking variable is different to the outcome measure. It uses a measure of living standards, in this case a household wealth index, and a measure of health, in this case under-five mortality rate (U5MR). U5MR and wealth index are aggregated over geospatial groups. Groups are ranked according to the living standards measure and plotted cumulatively on the x-axis. Proportion of the health measure, U5MR, for each group is plotted cumulatively on the y-axis. If U5MR is distributed equitably between districts of differing living standards then the plot will follow a 45 degree line from the origin. Inequity in U5MR favoring districts with higher median wealth indices results in a curve above this line, as shown in the three curves illustrated in Figure 3.1. The concentration index is calculated as double the area between the curve and the line of equity. This is calculated as:

$$IDCI = 1 - 2\int_{0}^{1} h(s)ds \qquad (1)$$

where h(s) is cumulative proportion of U5MR as a function of the cumulative share of districts ranked by living standards (median wealth index). This is negative when the function lies above the 45 degree line and positive when it lies beneath. The IDCI expression can be reformulated in regression format, as shown by Kakwani, Wagstaff and van Doorslaer [51] who derived the formula:

$$2\sigma_r^2\left(\frac{h_i}{\mu}\right) = \beta_0 + \beta_1 r_i + \varepsilon_i \qquad (2)$$

Where r_i is the fractional rank and σ_r^2as the variance of the fractional rank, hi is the mortality measure for district i and μ is the mean mortality over all districts. The β_1 estimate is the IDCI. Fractional ranks are adjusted to reflect weights for each district, so $r_i = \sum_{j=0}^{i-1} w_j + \frac{w_i}{2}$ where w_i is the weight for group i. The regression can be expanded to include other covariates. This results in the indirectly standardized estimate of IDCI:

$$2\sigma_r^2\left(\frac{h_i}{\mu}\right) = \beta_0 + \beta_1 r_i + \beta_2 X_i^T + \epsilon_i \qquad (3)$$

where X_i^T is a vector of controls and β_2 is the vector of corresponding coefficients. IDCIs have been calculated with and without population weighting. Primary results are based on unweighted values since the district is the unit of analysis and our main interest is in detecting the effects of place, regardless of the population of that place. District population is included as a covariate in expanded regressions.

Linear comparison of IDCIs does not take account of differences between two concentration curves across the distribution of districts. Therefore a measure of statistical dominance is used, which is a method of ordering used in decision theory when there are ambiguous differences between two measures [52]. In this analysis, it measures statistically significant difference between two times or states taking into account differences across the entire curve. Figure 3.1 compares three possible states, two of which have ambiguous differences. States A and C have concentration curves that dominate State B as they are above that of state B at every section of the curve, assuming that these differences are found to be statistically significant. However State C concentration curve crosses over that of State A and therefore neither is statistically dominant. This analysis tests for significant differences at 19 evenly-spaced points along the curve, implemented using the user-defined Stata program glcurve [39]. Subsets of the curve can also be compared, for example. State C has a higher proportion of mortality among the poorest 40% of districts than state A but also a higher proportion of mortality among the richest states.

The Slope Index of Inequality (SII) is calculated in Appendix 2 as a consistency check of the main IDCI indicator. SII is another measure that captures socio-economic inequalities across an entire population and is widely applied [53, 54]. This method regresses district U5MR on median district wealth index using a weighed least squares approach. The cumulative number of districts with each rank or lower is divided by the total number of districts. The mortality variable is then regressed upon this proportion and the slope of the regression line is the SII. It is interpreted as the absolute effect on mortality of moving from the lowest to the highest median income level [54]. This method was implemented using the Stata user-defined program riigen [55].

Spatial correlation was calculated using the R package "sp". Shapefiles for states and districts of India were downloaded from the Global Administrative Areas website (http://www.gadm.org) and attribute data for mortality and wealth indices were merged in from sources described above. Moran's I tests were conducted and spatial correlograms were constructed using the sp and maptools packages. R version 3.3.2 was used throughout the analysis [56].

Descriptive analysis

The primary analysis was based upon an analytic dataset of 600 districts in 27 states and 7 union territories for which mortality rates and wealth index were available. Mortality data was not available for one state, Nagaland. For 47 districts that came into existence between the 2001 and 2011 census, a wealth index could not be calculated for the earlier time period. Summary statistics of all districts included in the analysis can be seen in Table 3.1.

In the state-by-state analysis, five territories and three states were excluded from the analysis due to the fact that they contain 5 or fewer districts, which is insufficient to demonstrate inter-district inequality. The territories were (1)Andaman and Nicobar Islands, (2)Chandigarh, (3)Dadra Nagar Haveli, (4)Daman and Diu, (5)Lakshadweep and the states were (1) Goa, (2) Sikkim and (3)Tripura. Three smaller states did not have mortality data broken down by district, namely Meghalaya, Manipur and Mizoram and were excluded from the analysis. The state of Telangana was created in 2012 consisting of 10 districts that were previously in Assam, these have been included in Assam for the state-by-state analysis. Table 3.2 outlines the exclusions from each stage of the analysis. After all exclusions, this analysis encompassed 22 states containing 555 districts in total. The U5MR and wealth index profile of these districts was similar to that of the national level analysis, suggesting that none of the key variables are predictors of missingness. Comparison of all independent variables used in the analysis and tests for significant differences can be seen in Table 3.1.

Results

The national Inter-District Concentration Index (IDCI) reveals geospatial inequalities in U5MR across the entire country associated with our aggregate measure of district wealth. These were statistically significant in both 2001 and 2012. The IDCI can be interpreted as representing the proportion of wealth that would have be transferred from rich to poor states to achieve U5MR equality, which was 6.7% in 2001 and 10.7% in 2012. The inter-district concentration curves are shown in Figure 3.2. Tests of dominance showed that the concentration curve in 2012 statistically dominated that of 2001, meaning that inequality has increased statistically significantly across the entire population of districts.

To test the robustness of these results to the measures of under-five mortality and mortality inequality used in the analysis, we repeated the analysis using alternate indicators and methods. We conducted a similar analysis using only data from DLHS-2 and DLHS-3. These surveys contain only summary birth histories, so instead of basing concentration indices upon mortality rates, they are based upon Summary Birth History ratios. This is clearly a different measure to U5MR however it is interesting to measure inequality in this measure to see if it presents a comparable picture. The ratio of CD/CEB has been shown to theoretically correlate with U5MR, however this relationship is highly dependent on the quality of the SBH data [57].

To adjust for social and demographic factors additional variables can be included in the regression form of the concentration index to analyze inequality [39, 53]. The national level analysis was repeated including demographic and social characteristics, including population, education, religion and urbanicity. Women's education (average number of years) is negatively associated with geospatial inequity and is statistically significant across all model specifications. The measure of urbanicity used is the proportion of rural households in the district which is negatively associated with inequity, and is significant in most specifications. After adjusting for these district characteristics the IDCI reduces by almost half, but remains statistically significant. Some indicators that may be expected to correlate with U5MR did not show significance, for example access to improved toilet facilities. Region dummies showed significant differences from the North (reference region) in most specifications for all regions except the northeast.

The aggregation of districts across state lines in a national-level analysis may disguise subnational variation and trends, and national analysis shows significant variation by region. This issue can be particularly salient when measuring inequality between sub-populations therefore we analyzed IDCI by state to understand this geospatial variation [58]. This level of analysis may also be interesting to state level policymakers and to researchers looking at the effects of policies, public health expenditures and redistribution programs at a sub-national level. As described above, some states were dropped from the analysis for this stage as they had too few districts for the model to be valid. The results of this analysis are summarized in Figure 3.3, which shows a general upward shift in the distribution over the time period. This may be due to increasing inequality in under-five mortality rates associated with district wealth, however this requires further investigation by looking at individual states and decomposing for other factors. The median concentration of U5MR increased by 29% and first quartile increased by 80%. The inter-quartile range decreased by 13% but the difference between maximum and minimum inequality observed increased by 69%. Figure 3.4 maps these state level IDCIs in 2012.

Inter-district inequality was statistically significant in 73% of the analyses, with only four states having non-statistically significant inequality at both time periods. The highest level of inequality at state level was found in Karnataka, where more than 13% of wealth would have to be redistributed from rich to poor districts to achieve equality in under-five mortality rates. Karnataka is home to Bangalore and has some of the wealthiest districts alongside some of the poorest and highest mortality districts. Orissa (Odisha) had the second largest levels, followed perhaps surprisingly by Kerala which has been known for its 'miracle' in good health indicators achieved without commensurate economic growth [36, 37]. This is due to increased disparities in wealth and mortality between inland and coastal districts despite the overall level of mortality still being low at 13.2 per 1,000 live births in 2012, among the best in the country. For example, Kannur district on the coast had an under-five mortality rate of 8.8 in 2012 compared with inland Wayanad district, which had a rate three times this. IDCI increased in 68% of states, 15 of the 22 districts, suggesting that the association between the wealth of a district and survival of its children has strengthened over the first decade of the 21st century. A list of districts and their IDCI for each time period can be seen in Table 3.4, ranked in decreasing order of health inequity in 2012.

There is no clear spatial pattern of IDCI by state and no significant association is found between adjacent states in Moran's I tests, however there is significant clustering in district U5MR as shown in Figure 3.5. The heterogeneity of each state, with a unique combination of rich and poor districts with low and high U5MRs, and the small number of states in total make this result unsurprising. Districts of particular interest in this analysis are those with the worst wealth and U5MR indicators. Figure 3.6 highlights districts with very high U5MR and low wealth indices as well as those with very low U5MR and high wealth indices. There is again clear spatial clustering in central and north eastern states, however this is not reflected in high state level IDCIs as these states don't have the wealthiest, low mortality districts. In contrast, Karnataka has districts at both ends of the spectrum, contributing to its high IDCI. Relatively large IDCIs in Kerala appear to be driven by well-performing wealthy districts rather than the reverse, demonstrating the different challenges facing state and district policymakers in achieving U5MR equity.

Discussion

National level results indicate that statistically significant geospatial inequities exist in under-five mortality rates between districts in India. These are significant at both time periods and the statistical dominance of the 2001 concentration curve by that in 2012 indicates that inequity is becoming larger over time. These findings are consistent with other studies of U5MR and health inequity in India including in previous research using Census data which ranked districts using proportions of workers in agricultural work [23]. Decomposition of the national analysis in Table 3.3 suggests that U5MR inequities remain statistically significant after adjusting for social factors. Some of these factors are significant in the model, including the average education level of women in the district, whether the head of household was employed the previous year, and living in a district with a high proportion of rural households.

Tables 3.3a and 3.3b repeat the analyses in Table 3.3 for the most urbanized half and least urbanized half of districts separately. The motivation for this comparison was that the set of assets held by a 'typical' household may be different in a rural area than an urban area. Stratification results show no loss in significance of the IDCI, with slightly lower IDCI in the urban half and higher IDCI in the rural half than the primary results. Comparison of the 25% most urban with the 25% most rural districts showed a similar pattern, demonstrating a level of robustness of the IDCI to the level of urbanization of districts.

State level analyses find interesting variation around the country and IDCIs in 2001 and 2012 can be seen in Table 3.4 and Figure 3.4. The highest levels of inequity are found in

Karnataka, Orissa, Kerala and Andra Pradesh. Kerala is a surprising result here and demonstrates the value of disaggregation by state with respect to absolute level as well as internal variation. Its overall U5MR is among the lowest in the country, however the difference between its poorer and richer districts has increased between 2001 and 2012 and significant inequity has emerged. In Karnataka, the U5MR in urban Bangalore is low at 18.5 but rural district Raichur is more than four times this rate. While no spatial association is found between IDCIs at state level, U5MR at district level displays significant clustering, especially at extremes of the mortality and wealth distribution. Wealthier and healthier districts also seem to cluster along the coasts in most cases. Spatial analysis reveals high correlation between U5MR in neighboring districts, significant at multiple lags. The spatial association across state borders may be due to environmental or geographic factors that span multiple states, or spillover effects of state or regional policies. There is limited data available at district level, but state-by-state decomposition of available factors similar to the national decomposition here may reveal social or demographic drivers of inequality.

Major progress towards achieving MDG4 (the reduction of child mortality by two-thirds) was made during the period covered by this analysis, with U5MR falling from 87.7 to 54.5 per 1,000 live births [33]. However these reductions have not been realized equally across states and districts of India. Ram and colleagues identified districts which saw greater and lesser reductions in U5MR and revealed large disparities in rates of decrease [13]. The largest improvements were seen in rich areas in Kerala, Tamil Nadu and Jammu and Kashmir, Goa and urban areas of Karnataka. Smaller improvements were observed in districts across Uttar Pradesh, Bihar, Madhya Pradesh and rural Karnataka. This analysis builds upon previous results and confirms that reductions are not equitable, with these U5MR disparities associated with the relative wealth of districts. The biggest gains in U5MR were made in wealthier areas, and differences between wealthy and poor districts increased over the period.

As the Indian government aims to achieve large scale reductions in U5MR, there may be a trade-off between the productivity of health investments and the equity with which they are distributed. The goals of absolute reductions in mortality, or increases in life expectancy or DALYs may be in conflict with targeting the poorest in health and resources. A major criticism of targeting 'efficiency' in terms of DALYs is their indifference to the distribution of outcomes [59]. Similarly, a single goal such as MDG-4 implicitly prioritizes aggregate gains over equity. Two challenges for policymakers related to this are (1) aggregate gains may be possible more cheaply or quickly by focusing health resources on wealthier populations and (2) wealthier populations may be better able to capture the benefits from interventions that don't exclusively target poor districts or individuals.

Trends in health care, including primary health care, in India appear to increasingly favour richer populations. Studies have shown decreasing public provision of health care along with a large expansion of private provision and rapidly increasing costs of treatment [60, 61]. Differences in health outcomes between rich and poor households have been linked to access to health care with basic utilization of services and quality measures much lower in poor and rural areas [22, 27]. This is reflected in the distribution of health workers, with per capita coverage more than four times higher in urban areas than rural areas [49].

Compounding this, many private sector health workers in rural areas and slums are unqualified [48]. These disparities in health care have a geospatial dimension that may contribute to the U5MR inequities we find. These trends, if they should continue, are likely to further accelerate the disparities in healthcare access between rich and poor districts that we see in our analysis.

Population-wide interventions may result simultaneously in absolute improvements in health and stagnating, or even increasing, inequity if wealthier districts can take advantage of available resources and services more readily than less wealthy districts. Victora and colleagues proposed an "inverse equity hypothesis", that certain health interventions targeting child health save more lives among wealthier populations even if that is not the intent [62]. They attribute this to greater education levels and financial capacity to access health services. As a case study, they consider a set of child health and nutrition programs in the late 1980s and early 1990s in Ceará, Brazil. Despite an overall improvement in child health indicators, these interventions failed to improve health inequities between rich and poor populations [63].

The efficiency versus equity decision may change over time, and already differs by state. Absolute gains will begin to slow in wealthy areas, for example in parts of Kerala some U5MRs are almost as low as they area in high-income countries. It may become more efficient to focus on worse-off areas where the mortality gaps remain high. The private sector is unlikely to drive this shift as research shows that private providers tend to provide additional services in rich areas rather than expanding reach to less populated, hard to reach districts with little resources and not attractive to skilled health workers [60]. A study in Pelotas, Brazil demonstrate general population-based child health interventions can reduce inequities, although this only occurs once the wealthier have reached a level of satiation and this assumes that services or health amenities are geographically accessible to both the rich and poor [64]. This analysis demonstrates that the geospatial scope of a policy or intervention can affect who benefits. By targeting poorer districts, geospatial equity should be ameliorated.

The inverse equity hypothesis does not necessarily apply to all population-wide child health interventions. Bishai, Koenig & Khan found that child health inequalities based on socio-economic status were reduced by a large measles immunization program in Matlab, Bangladesh [65]. Vaccination programs were found to be efficient, cost-effective and improve equity in India and Ethiopia and Vitamin A supplementation in Nepal [66, 67]. Other interventions that have successfully reduced inequities including targeted rural primary health care services, overall per capita health spending across several countries, and maternal education [68 -71]. The significance of maternal education in our analyses of inequity suggests that this may also be relevant in the context of India. Recent research on geospatially targeted interventions in rural India has also shown promise [72 - 75].

It is not clear, given the equity versus efficiency trade-off discussed above, whether there is ethical justification for prioritizing geospatial equity ahead of overall national and state reductions in U5MR. In absolute terms more child deaths occur every year in India than in any other country and this can be used to justify a policy focus on absolute reductions. If diverting health resources to wealthy districts can save more lives how can the government justify spending in poor districts? Equity must be as much a part of the decision as an aggregate goal such as MDG-4. This analysis shows that relative differences in U5MR are associated with the wealth of a district, a situation that may be driven by governmental action or inaction that is distributing health resources, personnel and emphasis away from the poor and towards the rich. These inequities are likely to be exacerbated over time as districts with fewer resources attract fewer quality health workers and private investment in health care. Lower incomes also mean a smaller tax base and fewer resources for investments in local health amenities, water and sanitation, education and environment, potentially compounding the negative effects on social determinants of health and widening health gaps between rich and poor places. Sen argues that the "assertive features" that Williams, Culyer and Wagstaff arrive at in their definitions of health equity are insufficient alone [31, 76, 77]. To capture the broader issues of social justice in health targets and health improvements, multiple interpretations of equity should be considered [76]. The geospatial measure of inequity in this analysis provides decision makers with another tool to compare the potential social outcomes of available policies and consider another dimension of health equity.

Limitations

There are some important limitations of this analysis that must be considered in the interpretation of findings. Just as grouping individuals by income can obscure the effects of place, grouping by place combines individuals across income groups and so can hide the effects of income at an individual level. Aggregation disguises geospatial inequities within districts that contain a lot of heterogeneity, for example slums within cities and heavily urban districts. The same type of analysis could be carried out at a more granular level, should data become available.

The reliability of U5MR estimates is also a limitation of the analysis. As no direct estimates exist at district level, the best alternative available were the indirect estimates from Ram and colleagues [13] which are designed to be consistent with good quality state level estimates from SRS and national UN estimates. These use summary birth histories to indirectly estimate district deaths using the Brass method and use these to proportion out state level deaths from full birth histories. Studies have indicated that the quality of summary birth histories may be too poor to base U5MR estimates on in some circumstances [57]. The Annual Health Surveys (AHS) provide estimates of U5MR over 9 states based on full birth histories, which is considered the gold standard for direct estimation in countries that lack vital registration systems. Correlation across these districts between the indirect estimates and AHS estimates was 57%, leaving some doubt as to the quality of estimates. This is a key source of risk as the variability in district level U5MR drives the analysis.

The wealth index itself has many flaws as a measure. A study of wealth indices applied in low- and middle-income countries showed limited correlation with consumption and varied in how well they represented socio-economic position. This was based on DHS surveys, whose wealth indices are constructed similarly to DLHS indices, and highlighted weaknesses of the principal components analysis method of assigning weights to specific assets. They found that its appropriateness to measure socio-economic position varied by subgroups of the population, for example slum dwellers versus rural poor have different patterns of assets held. To address the effect of this on our comparisons between urban and rural districts, a stratified analysis was conducted measuring effects in rural and urban districts separately as described in Results. Despite these disadvantages, wealth indices have been found to be significantly associated with living standards and represent a useful economic measure [79].

The definition of districts is frequently changing and new districts and even states have recently been created [26]. Changes that affect the national and state analysis have been documented in Table 3.2. One state is missing from the analysis, Nagaland, as data was not included in DLHS-3. It had a moderate U5MR of 58.7 in 2012 but variability between districts is not known. Similarly, district level variability in U5MR for Manipur, Mizoram, Meghalaya, Sikkim and Tripura was not included as there was either insufficient data to produce estimates. There may be characteristics of districts that are missing from both that are associated with either economic well-being or child mortality in the district. However in the states for which district data is available, there is very little missingness and so the results for these states are unlikely to be biased by missingness.

The combination of survey data from different years is an important limitation to the methods. Due to the limited data available, the asset scores from DLHS surveys apply to different years than those to which the mortality rates apply. This makes the assumption that the ordering of district wealth has not changed to a large extent between these two time periods. There is some evidence that wealth indices are quite stable over time [80]. As mentioned above, correlation between wealth indices showed high levels of consistency over time. In addition, the concentration index uses rankings rather than the scores themselves, and relative position is likely to be more stable than specific value. Therefore the assumption of stable median wealth indices between 2007 (DLHS-3) and 2012 may not be unrealistic enough to bias results.

Conclusions

This analysis found significant child mortality inequity between districts at both state and national level in India. Inter-district inequity is increasing over time and this can be seen in states with high and lower under-five mortality rates overall. This inequity is still statistically significant after other social and demographic features are adjusted for at district level. Improvements in U5MR over the period of analysis have been disproportionately realized in wealthier districts of India. This may be due to an emphasis on efficient investments to achieve absolute reductions in mortality in pursuit of the Millennium Development Goals at the expense of a focus on equity. Inequities may be sustained over time as those who can afford to move to healthier districts leave those that are less healthy, self-segregating by health and wealth. Health workers and health investments are shifting increasingly to wealthier urban areas, compounded by the growth in private sector healthcare relative to public healthcare. As these inequities continue to grow and marginal gains from health investments in wealthy areas decline, we may see more attention given to health inequities among policymakers and geospatial inequity is an important perspective to track and address.

Chapter 3 References

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Table 3.1: Summary statistics in 2012 for the 600 districts in the national-level analysis and the 555 districts in the state-level analysis

	Statistics for 600 districts in national analysis				Statistics for 555 districts in state-level analysis				Test for difference in means (p-value)
Statistic	**Mean**	**Std. Dev.**	**Min**	**Max**	**Mean**	**Std. Dev.**	**Min**	**Max**	
Under-5 Mortality Rate	55.21	22.37	8.8	152.6	56.22	22.69	8.8	152.6	0.47
Wealth Index (Standardized)	0.33	0.22	0	1	0.33	0.21	0	0.98	0.98
Population (000s)	2119	1541	8	11383	2143	1565	8	11383	0.77
Number of live births (000s)	43.8	31.8	0.2	195.4	44.9	32.2	0.2	195.4	0.56
Average number of years of mother's education in district	4.5	1.9	0.9	10.3	4.4	1.9	0.9	10.3	0.36
Percentage of district population members of a scheduled caste	17.6	9.0	0.0	55.4	18.4	8.6	0.4	55.4	0.27
Percentage of district population members of a scheduled tribe	17.8	25.7	0.0	99.7	14.8	21.5	0.0	95.3	0.22
Percentage of district population living in rural area	77.0	19.7	0.0	100.0	77.5	18.9	0.0	100.0	0.61
Percentage of district population that is illiterate	76.9	13.7	12.4	98.5	78.6	11.7	21.6	98.5	0.20
Percentage of district population in full-time employment last year	14.0	12.2	0.4	88.2	14.1	12.5	0.4	88.2	0.92
Percentage of district population that is Muslim	11.0	15.7	0.0	99.6	11.4	15.7	0.0	99.6	0.66
Percentage of district	6.2	18.2	0.0	99.8	3.2	9.6	0.0	82.6	0.15

population that is Christian									
Percentage of district population that is Sikh	2.7	12.3	0.0	93.4	2.9	12.7	0.0	93.4	0.78
Percentage of district population that is Buddhist	1.6	8.0	0.0	80.8	1.3	7.1	0.0	80.8	0.50
Percentage of households with no access to a toilet	54.8	29.4	0.0	96.0	57.9	27.8	0.4	96.0	0.23
Percentage of households with health insurance	4.9	6.6	0.0	48.1	4.7	6.5	0.0	48.1	0.75

Table 3.2: Diagram of district exclusions for each stage of the analysis

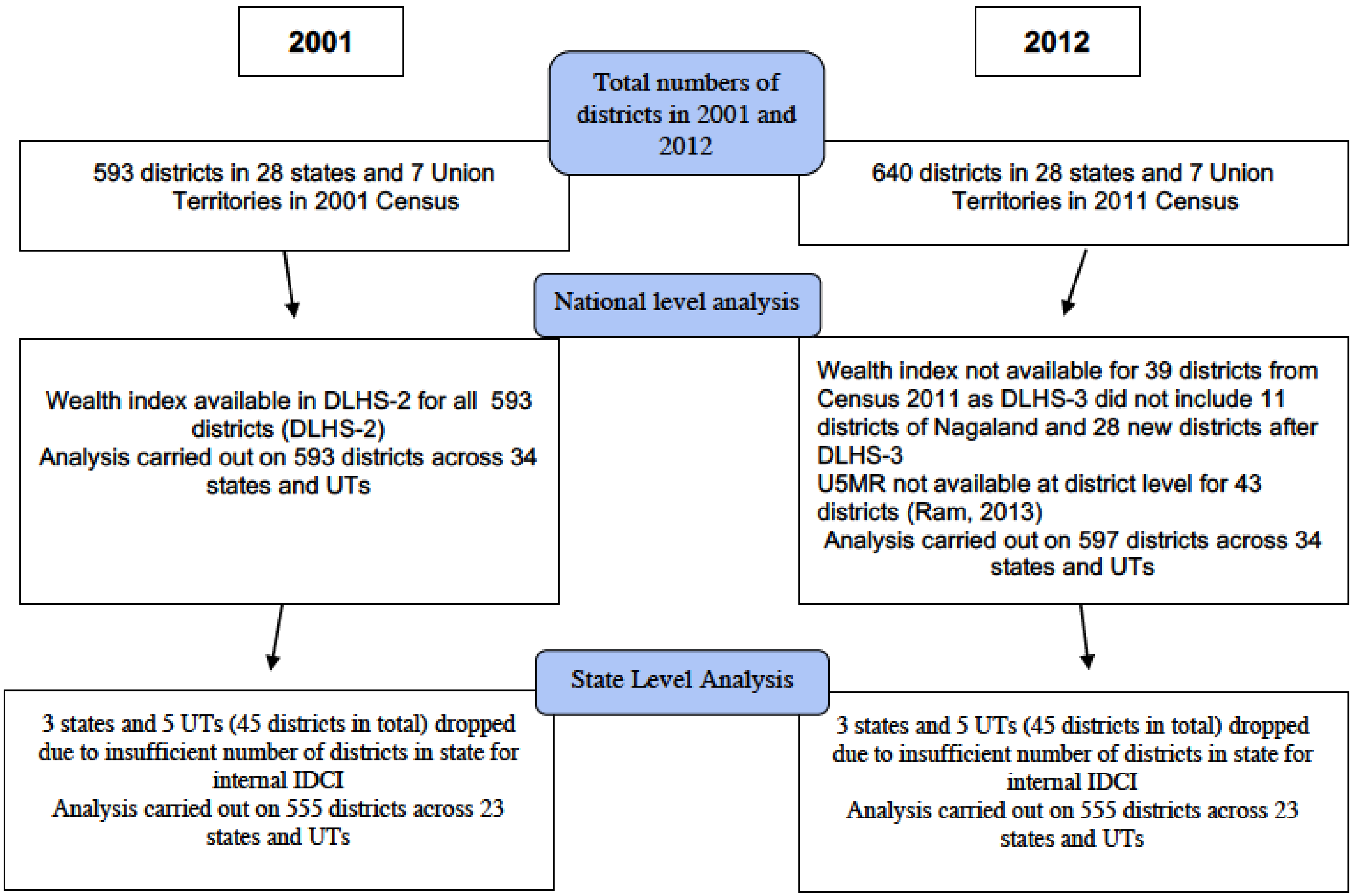


Table 3.3: National Inter-District Concentration Index adjusting for district U5MR determinants in 2012

		Basic IDCI	Including social and demographic factors in IDCI regression				
Ranking of District Median Wealth		-0.142*** [0.00770]	-0.157*** [0.00814]	-0.0875*** [0.0130]	-0.101*** [0.0138]	-0.104*** [0.0166]	-0.0960*** [0.0169]
Population (million)			-1.079 [1.271]	-2.221* [1.225]	-4.830*** [1.287]	-4.118*** [1.219]	-4.589*** [1.287]
Women's education level (Avg. number of years of education of mothers in the district)				-0.000125*** [1.57e-05]	-0.000122*** [2.08e-05]	-0.000117*** [1.99e-05]	-0.000114*** [2.16e-05]
Proportion of district households	Members of a scheduled caste				0.000298 [0.000295]	6.16e-05 [0.000243]	0.000311 [0.000296]
	Members of a scheduled tribe				8.42e-05 [0.000185]	3.07e-05 [0.000133]	7.62e-05 [0.000187]
	Living in rural area				-0.000559*** [0.000124]	-0.000592*** [0.000121]	-0.000545*** [0.000124]
	Illiterate (head of household)				0.000551** [0.000270]	0.000444** [0.000219]	0.000534** [0.000272]
	Employed last year (head of household)				-0.000582*** [0.000180]	-0.000510*** [0.000180]	-0.000534*** [0.000181]
	Muslim (head of household)				8.99e-05 [0.000174]		0.000164 [0.000192]
	Christian (head of household)				0.000123 [0.000256]		0.000152 [0.000251]
	Sikh (head of household)				-0.000225 [0.000137]		-0.000167 [0.000142]
	Buddhist (head of household)				-0.000347 [0.000294]		-0.000297 [0.000289]
	No access to toilet					0.000143 [0.000160]	0.000165 [0.000174]
	With health insurance					0.000460 [0.000298]	0.000479 [0.000299]
South dummy			-0.0499*** [0.00470]	-0.0531*** [0.00518]	-0.0540*** [0.00514]	-0.0555*** [0.00548]	-0.0657*** [0.00463]

East dummy		-0.0353*** [0.00687]	-0.0371*** [0.00669]	-0.0370*** [0.00677]	-0.0363*** [0.00677]	-0.0508*** [0.00643]
West dummy		-0.0149*** [0.00537]	-0.0136** [0.00621]	-0.0174*** [0.00609]	-0.0154** [0.00632]	-0.0243*** [0.00542]
Northeast dummy		0.0120 [0.00836]	0.0136 [0.0103]	0.0214* [0.0116]	0.0199* [0.0115]	-0.00771 [0.00840]
Number of districts	600	597	597	597	597	597
R^2	0.370	0.507	0.547	0.584	0.583	0.586
Interpretation of wealth ranking coefficient: % of mortality required to transfer from poor to rich states for IDCI to equal zero	10.7%	11.8%	6.6%	7.6%	7.8%	7.2%

Table 3.3a: Inter-District Concentration Index for Urban half of districts adjusting for district U5MR determinants in 2012

		Basic IDCI	Including social and demographic factors in IDCI regression				
Ranking of District Median Wealth		-0.154*** [0.0119]	-0.183*** [0.0112]	-0.113*** [0.0169]	-0.112*** [0.0194]	-0.0982*** [0.0209]	-0.0943*** [0.0211]
Population (million)			0.594 [1.383]	-0.395 [1.313]	-1.707 [1.435]	-0.834 [1.372]	-1.245 [1.390]
Women's education level (Avg. number of years of education of mothers in the district)				-0.000115*** [1.73e-05]	-0.000127*** [2.34e-05]	-0.000124*** [2.37e-05]	-0.000107*** [2.57e-05]
Proportion of district households	Members of a scheduled caste				-0.000214 [0.000393]	-0.000407 [0.000295]	-0.000229 [0.000393]
	Members of a scheduled tribe				1.38e-05 [0.000265]	2.51e-05 [0.000175]	-2.48e-05 [0.000254]
	Living in rural area				-0.000285** [0.000133]	-0.000361*** [0.000133]	-0.000297** [0.000136]
	Illiterate (head of household)				0.000471 [0.000393]	4.12e-06 [0.000259]	0.000366 [0.000371]
	Employed last year (head of household)				-0.000606* [0.000332]	-0.000579 [0.000419]	-0.000679** [0.000324]
	Muslim (head of household)				0.000101 [0.000285]		0.000442 [0.000312]
	Christian (head of household)				0.000470 [0.000362]		0.000475 [0.000350]
	Sikh (head of household)				-0.000128 [0.000155]		6.24e-05 [0.000160]
	Buddhist (head of household)				-0.000417 [0.000555]		-0.000176 [0.000502]
	No access to toilet					0.000457** [0.000191]	0.000539** [0.000221]
	With health insurance					0.000741** [0.000316]	0.000757** [0.000323]
South dummy			-0.0819*** [0.00532]	-0.0640*** [0.00597]	-0.0638*** [0.00680]	-0.0684*** [0.00660]	-0.0689*** [0.00717]
East dummy			-0.0549*** [0.00951]	-0.0360*** [0.00988]	-0.0357*** [0.0103]	-0.0369*** [0.00964]	-0.0340*** [0.0102]

West dummy		-0.0370*** [0.00663]	-0.0267*** [0.00660]	-0.0245*** [0.00811]	-0.0319*** [0.00783]	-0.0276*** [0.00811]
Northeast dummy		-0.0195 [0.0128]	-0.000191 [0.0132]	-0.0123 [0.0171]	0.00947 [0.0168]	0.00845 [0.0177]
Number of districts	297	295	295	295	295	295
R^2	0.338	0.583	0.624	0.650	0.655	0.663
Interpretation of wealth ranking coefficient: % of mortality required to transfer from poor to rich states for IDCI to equal zero	11.6%	13.7%	8.5%	8.4%	7.4%	7.1%

Table 3.3b: National Inter-District Concentration Index for Rural half of districts adjusting for district U5MR determinants in 2012

		Basic IDCI	Including social and demographic factors in IDCI regression				
Ranking of District Median Wealth		-0.150*** [0.0129]	-0.200*** [0.0157]	-0.132*** [0.0225]	-0.132*** [0.0224]	-0.142*** [0.0272]	-0.134*** [0.0275]
Population (million)			-7.146*** [2.389]	-8.320*** [2.345]	-10.53*** [2.584]	-9.952*** [2.462]	-10.73*** [2.673]
Women's education level (Avg. number of years of education of mothers in the district)				-0.000122*** [2.59e-05]	-0.000103*** [3.46e-05]	-0.000102*** [3.48e-05]	-0.000108*** [3.59e-05]
Proportion of district households	Members of a scheduled caste				0.000795* [0.000457]	0.000447 [0.000397]	0.000779* [0.000460]
	Members of a scheduled tribe				4.30e-05 [0.000242]	2.69e-06 [0.000175]	3.98e-05 [0.000243]
	Living in rural area				-0.00199*** [0.000686]	-0.00197*** [0.000689]	-0.00201*** [0.000698]
	Illiterate (head of household)				0.000585 [0.000401]	0.000599 [0.000365]	0.000585 [0.000399]
	Employed last year (head of household)				-0.000520** [0.000260]	-0.000485* [0.000251]	-0.000556** [0.000270]
	Muslim (head of household)				0.000179 [0.000211]		0.000148 [0.000214]
	Christian (head of household)				0.000136 [0.000330]		0.000121 [0.000321]
	Sikh (head of household)				-0.000794*** [0.000186]		-0.000827*** [0.000201]
	Buddhist (head of household)				2.91e-05 [0.000369]		2.20e-05 [0.000368]
	No access to toilet					-0.000103 [0.000238]	-7.85e-05 [0.000239]
	With health insurance					-0.000211 [0.000607]	-0.000239 [0.000611]
South dummy			-0.0486*** [0.0101]	-0.0367*** [0.00889]	-0.0453*** [0.0114]	-0.0421*** [0.0112]	-0.0439*** [0.0118]
East dummy			-0.0537*** [0.00826]	-0.0405*** [0.00913]	-0.0373*** [0.00887]	-0.0379*** [0.00931]	-0.0377*** [0.00920]

West dummy		-0.0326*** [0.00944]	-0.0224** [0.00946]	-0.0148 [0.0112]	-0.0172 [0.0110]	-0.0138 [0.0118]
Northeast dummy		-0.000810 [0.0109]	0.0176* [0.0104]	0.0260** [0.0127]	0.0244 [0.0160]	0.0229 [0.0157]
Number of districts	302	301	301	301	301	301
R^2	0.292	0.425	0.461	0.508	0.503	0.508
Interpretation of wealth ranking coefficient: % of mortality required to transfer from poor to rich states for IDCI to equal zero	11.3%	15.0%	9.9%	9.9%	10.7%	10.1%

Table 3.4: Ranked Inter-District Concentration Index across 22 states of India in 2001 and 2012

	2001			2012			
State	**Inter-District Concentration Index**	**Standard Error**	**p-value**	**Inter-District Conc. Index**	**Standard Error**	**p-value**	**2012 >2001 concentration curve[a]**
Karnataka	-0.107	[0.0157]	<0.01	-0.175	[0.0314]	<0.01	Yes
Odisha	-0.0602	[0.0142]	<0.01	-0.119	[0.0220]	<0.01	Yes
Kerala	-0.0206	[0.0182]	>0.1	-0.111	[0.0476]	<0.05	Yes
Andhra Pradesh	-0.0976	[0.0206]	<0.01	-0.109	[0.0212]	<0.01	No
Gujarat	-0.0626	[0.0193]	<0.01	-0.103	[0.0335]	<0.01	Yes
Maharashtra	-0.096	[0.0208]	<0.01	-0.103	[0.0174]	<0.01	Yes
Jammu & Kashmir	-0.0913	[0.0555]	>0.1	-0.101	[0.100]	>0.1	No
Himachal Pradesh	-0.0534	[0.0243]	<0.1	-0.0853	[0.0399]	<0.1	Yes
Madhya Pradesh	-0.0434	[0.0142]	<0.01	-0.0747	[0.0182]	<0.01	Yes
West Bengal	-0.0179	[0.0273]	>0.1	-0.073	[0.0268]	<0.05	Yes
Jharkhand	-0.0721	[0.0189]	<0.01	-0.0716	[0.0240]	<0.01	No
Assam	-0.0635	[0.0167]	<0.01	-0.0707	[0.0330]	<0.05	No
Chhattisgarh	-0.0347	[0.0150]	<0.05	-0.0606	[0.0164]	<0.01	Yes
Tamil Nadu	-0.00965	[0.0158]	>0.1	-0.0589	[0.0224]	<0.05	Yes
Arunachal Pradesh	-0.0957	[0.0602]	>0.1	-0.0547	[0.0467]	>0.1	No
Haryana	-0.0289	[0.0144]	<0.1	-0.0542	[0.0351]	>0.1	No
Uttar Pradesh	-0.057	[0.00739]	<0.01	-0.0526	[0.0101]	<0.01	No
Rajasthan	-0.101	[0.0154]	<0.01	-0.0454	[0.0168]	<0.05	No
Delhi	-0.0225	[0.0125]	>0.1	-0.0307	[0.0346]	>0.1	No
Bihar	-0.0311	[0.0129]	<0.05	-0.0282	[0.0140]	<0.1	No
Punjab	-0.0343	[0.0144]	<0.05	-0.00467	[0.0304]	>0.1	No
Uttarakhand	-0.0234	[0.0338]	>0.1	0.0103	[0.0522]	>0.1	No

[a]Concentration curve of 2012 dominates that of 2001 if 19 evenly spaced points along the curve are statistically significantly greater. States whose inequality (measured by IDCI concentration curve) has not statistically significantly increased, or has reduced, are in italics.

Figure 3.1: Sample dominant and non-dominant concentration curves

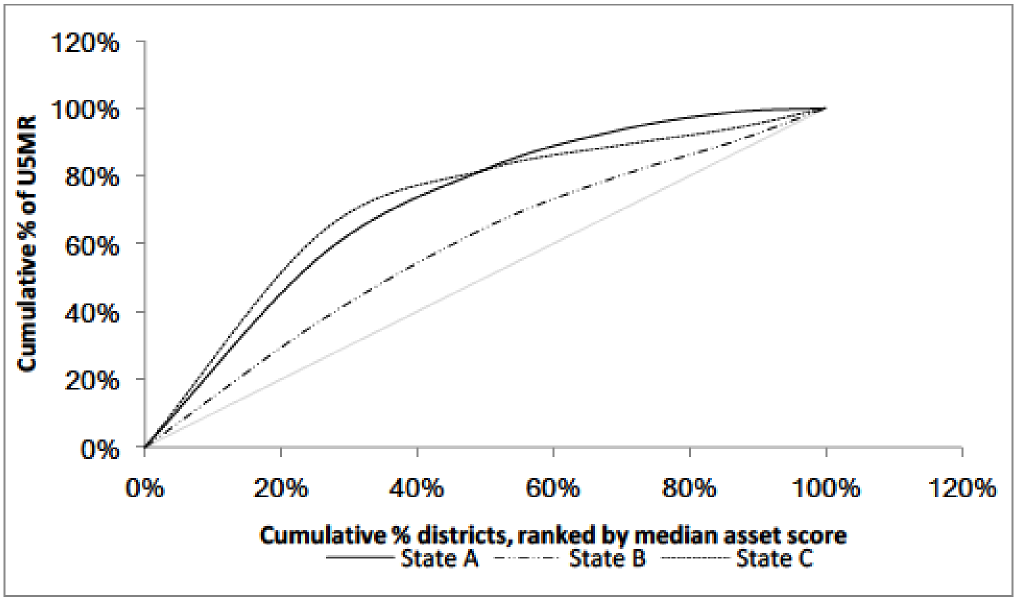
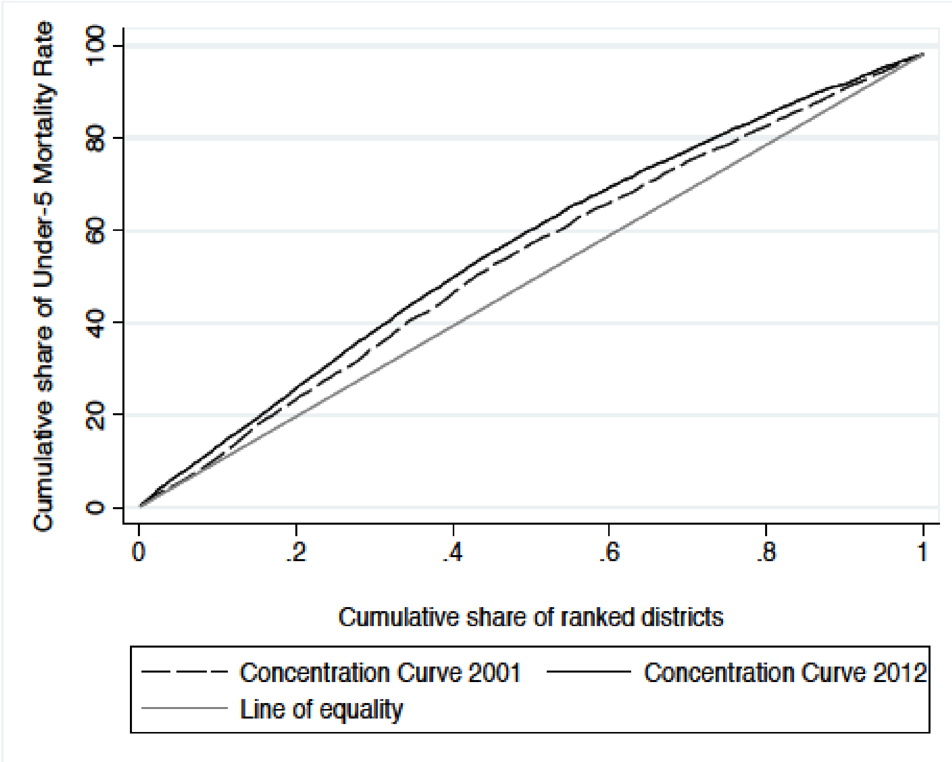


Fig 3.2: Inter-District Concentration Curve of U5MR for India in 2001 and 2012



$IDCI_{2001}$ = 6.7%
$IDCI_{2012}$ = 10.7%

Note: $IDCI_{2001}$ denotes the interpretation of IDCI, ie. the percentage of U5MR required to be redistributed from poor districts to wealthy districts to achieve equality

Figure 3.3: The distribution of Inter-District Concentration Indices in 2001 and 2012

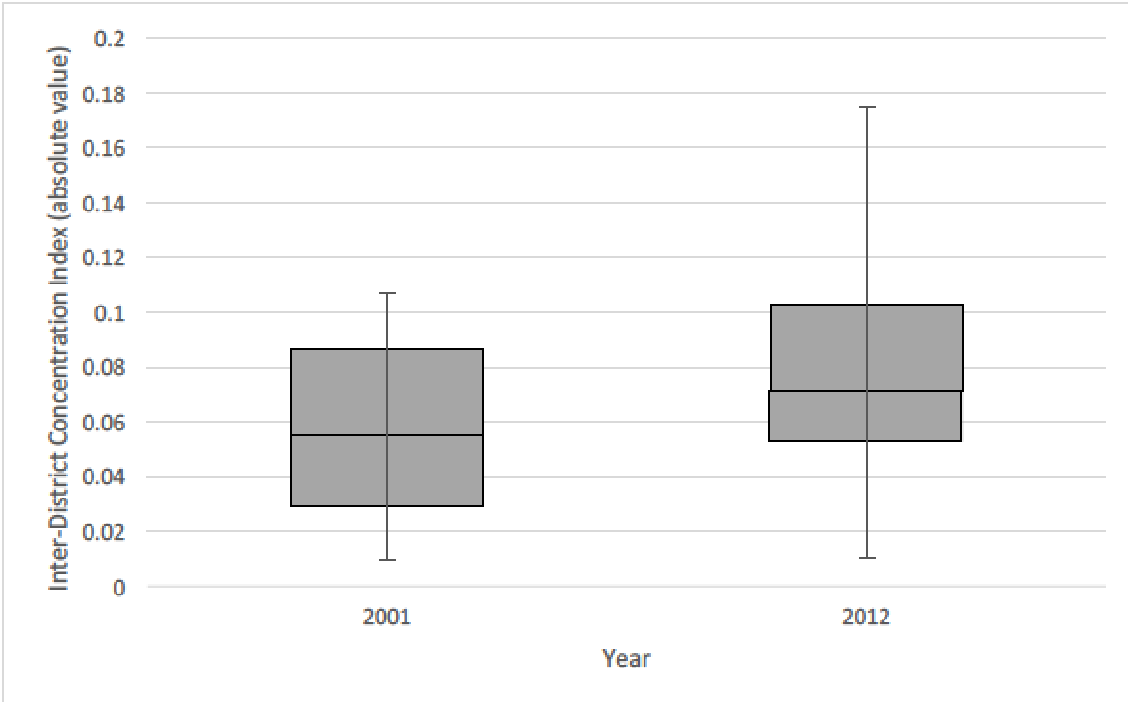


Figure 3.4: Inequity by state in 2012: Percentage of U5MR that would need to be redistributed from rich to poor districts for an IDCI of zero in each state

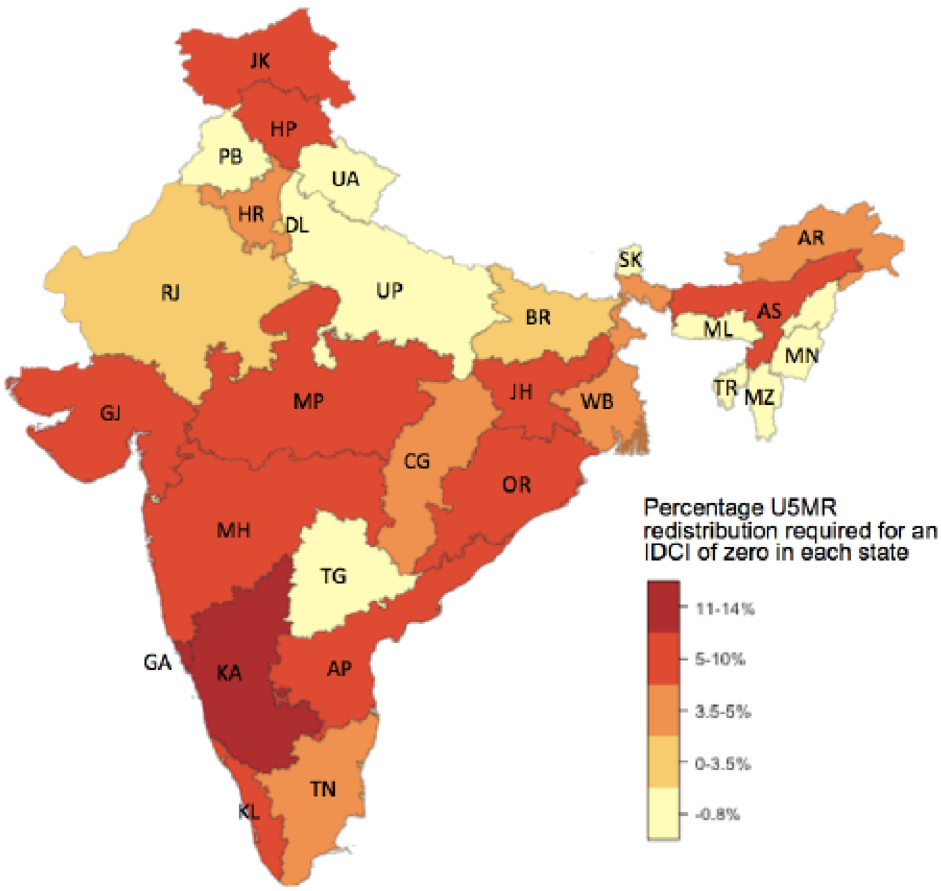
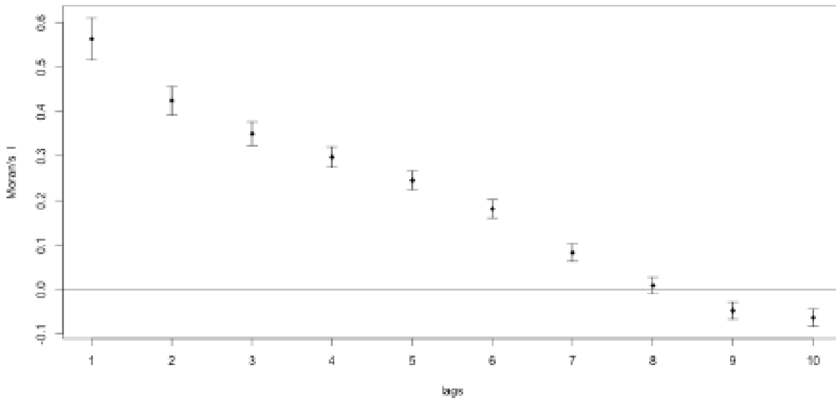
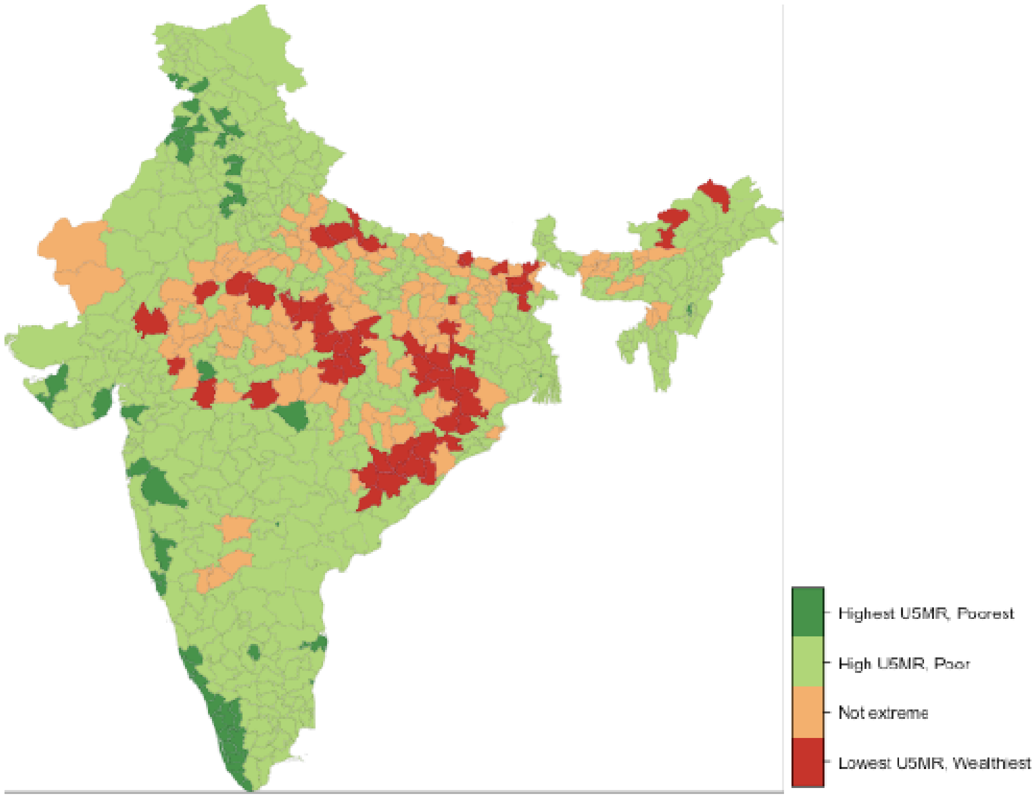


Figure 3.5: Correlogram of district spatial lags[a] in district U5MR



[a] A district at a spatial lag of 1 to district A is defined as any district B that is directly contiguous, with 1 or more points of contact to district A ('queen' contiguity). Districts at a spatial lag of 1 to district B (other than district A) are at a spatial lag of 2 to district A.

Figure 3.6: Map of districts at the extremes of the U5MR and wealth index distributions



Chapter 4 (Manuscript 3): Can US state governments redistribute health between counties?

Introduction

Significant health inequalities between counties exist in most US states, with income-driven mortality differentials increasing significantly in recent decades [1, 2, 3]. A geospatially-defined measure of inequality can be useful to policymakers who aim to reduce these mortality inequalities, both by observing and tracking these inequalities, and by observing associations between policies and measures of inequality.

This research proposes inter-governmental transfers from state to county governments in the US as a mechanism through which geospatial inequities can be addressed. We propose a conceptual framework through which states can redistribute resources to reduce health inequities between its richer and poorer counties. We then construct a panel model to estimate the association between State-to-County Transfers (SCTs) from each state to its constituent counties and geospatial health inequity within those states, measured by the Inter-County Concentration Index of mortality inequity over the period 1972 to 2012. The associations between health inequity and other spending at county level, as well as demographic characteristics, were included in the analysis.

Background

The literature on mortality inequalities in the US has largely looked at disparities by income, race or educational groups [4, 5, 6] with some focus on geographic, environmental and behavioral risk factors [2, 7, 8]. There has been little published research on policies and interventions with the explicit purpose of reducing geospatial inequalities at a national or state level. Sen argued that any single perspective of health equity is insufficient alone [9], just as Krieger argued that any single definition of a population can be misleading depending on the context [10]. The importance of considering a geospatial perspective can be seen from recent research by Dwyer-Lindgren and colleagues, mapping causes of death maps by US county, and Brady (Chapter 2) findings that the geospatial disparities are significantly associated with county median income [1, 11].

The Inter-County Concentration Index (ICCI) exists because counties with higher income and higher taxes can afford to provide greater health amenities. This leads to a stratification of counties by health and income, with low mortality, high income counties bordering on high mortality, low income counties. A high ICCI is a public health challenge worthy of policymakers' and researchers' attention for several reasons. Firstly, stratification by income means fewer resources are available in counties with the least health amenities. As the differences in public investments are sustained over time, disparities in such amenities are likely to grow, leading to a cycle of increasing inequity [12, 13]. Geospatial inequities are realized in physical boundaries between rich, healthy counties and poor, sick ones. The frequent exposure of disadvantaged populations to advantaged populations has been shown to result in toxic stress and has psychological health implications [14, 15, 16]. Finally, there may be fiscal inequities as social benefits realized during older ages are likely to be captured by longer-living rich sub-populations while being funded by the state-wide tax base [17, 18, 19].

Given that the reduction of ICCIs should be a policy priority for state and federal policymakers, the tools that they have at their disposal to address ICCIs should be considered. Individually-targeted programs such as Medicaid can be used to reduce inequality at an individual level by improving access based on means-testing. County and state resource allocation can be used to reduce geospatial inequities by directing resources to lower-income, poorer health counties.

There is evidence that public investments in health amenities have the potential to redistribute health among communities. Or found in an extensive study of OECD countries, that social and environmental factors are more important to health outcomes than medical inputs [20]. A recent systematic review finds that public health spending has the potential to improve health in the communities where these investments are made [21]. Pathways are not entirely clear and knowledge of local needs is important. Recent research has suggested that the physical, social and economic environment that families live in may be particularly important to mortality inequalities as lower-income groups benefit disproportionately from living in a high-income area [2]. This may be due to better provision of health amenities in these areas by local governments. Recent studies have found significant effects of public health spending at county level upon all-cause mortality in individual states and nationally [22, 23, 24]. A recent study examining the relationship between non-hospital health spending and life expectancy at county level demonstrates that the association varies greatly by state, and when effective can have quite a large effect size [22]. By increasing geographically-targeted investments in public health amenities and services, a state government can improve health production in counties that lack sufficient individual investments and over time this has the potential to reduce geospatial mortality inequalities.

This analysis is focused on State-to Local Transfers (SLTs) as a geospatial channel of redistribution. Every year, states transfer resources to county governments for public expenditures. Much of this is earmarked for particular programs, some is not. If the inter-county mortality inequity based on income described above is seen as a problem within a state, state-to-local transfers can be used to rebalance resource availability at county level and provide relative improvements in health-related amenities in the counties that are disadvantaged in terms of mortality. A recent study examining state-to-county transfers over the period 2000-2013 found that approximately 30% of transfers were for public health and large percentages were for behavioral health, disability care and environmental protection [25]. There is evidence that shifting resources from central management to local management can have significant health benefits. Fiscal decentralization in China has led to more efficient production of local public goods [26]. It has resulted in the improvement of infant mortality rates in Canada and rural India [27, 28]. Ransom and colleagues found in the US that tailoring public health programs to local needs improved immunization rates [29].

State and county expenditures on public health, safety and healthcare expenditures are channels through which state governments can improve health equity within their states. Individuals with higher income levels achieve better health, and income-based mortality inequalities are common [2, 30]. Tiebout theory predicts that people self-sort to locations based on preferences for the amenities and tax regimes attached to a given community [31]. This is a familiar concept in education, with local migration between school districts to improve children's education, subject to their ability to buy property in a school districts that is perceived as successful [32]. We hypothesize that on the margin, some households choose to live in places with better public health amenities, and move to maximize their utility subject to preferences and ability to pay. This results in sustained, and potentially exacerbated, health inequalities as populations are self-segregated geospatially according to their income and preference profiles.

Methods

Conceptual Framework

Health inequities are defined as avoidable or unjust differentials in the health status of populations [33, 34, 35]. Geospatial health inequities are those that exist between geo-spatially defined populations, such as county, city, commuting zone or census tract populations. These arise when inequalities in health result from differences in the composition of such populations in terms of income, education, race or another characteristic whose effect on health outcomes is not ethically justifiable or avoidable (in contrast with, for example, age) [12, 36]. The Inter-County Concentration Index measures inequalities in age-adjusted mortality rates between counties in US states, based on their association with the unequal distribution of income between counties. Therefore mortality inequalities in a state that are evenly distributed across its counties would result in a zero

ICCI. In contrast, a state with high mortality in low income counties and low mortality in high income counties would have a high ICCI.

The conceptual framework for this analysis is based upon resource distribution across counties. In each county, local government collects revenues from its own internal sources, primarily taxes. States distribute additional resources from federal and state taxes to supplement local resources. The local government has information on the public health needs and preferences of its constituent population. These three factors combine to generate a distinct profile of public health amenities for each district. Households face the decision to choose from a set of counties with associated health amenities and taxes. We assume they choose based on their preference for health amenities and their ability to pay (income). If we assume that preferences for health are homogeneous, this results in self-sorting by income as those who can afford to pay more to live in counties with better health amenities do so. This results in geospatial inequities, where those with higher income live in counties with better health amenities and vice-versa. Figure 4.1 describes this process visually.

The relative amount of resources transferred to counties will affect health equity as each county benefits differently. By increasing SLTs to a county with low taxes and few health amenities and decreasing SLTs to a county with high taxes and better health amenities, the decision faced by households is altered. Health amenities in the poorer county can be increased without increasing the cost of living there, which should improve health outcomes in these counties and reduce geospatial health inequity.

The hypothesis of this study is that geospatial equity, and reduction of ICCI in particular, is an aim of state and federal level policymakers. Therefore they will divert resources to counties with the greatest need. This will mean that transfers from state to local government should result in improved equity within states.

Data

Government expenditure variables, including SCTs, are taken from the US Census of Local Governments, which contains public health and other spending variables collected every 5 years from 1972 to 2012 for 50 states and the District of Columbia. Annual routine data collection by the Census includes revenue, expenditures and debt across all functions and levels of government, with a full census at county level every 5 years. Expenditures are itemized across programs and revenues are classified by source and all expenditures were adjusted for inflation [37]. Details on the data from the Census of Governments can be found at: https://www.census.gov/govs/. The primary independent variable for this analysis was the SCT which was calculated as the difference between the variables 'General Revenue' and 'General Revenue Own Sources'. These are county level variables and include state funding of counties as well as federal funding that is channeled through the state. County expenditures for all social program areas were summed for each state. The county social spending variable was defined as the state total for spending on itemized program areas: Education, Public Health and non-hospital healthcare, Hospitals, Housing and Community Development, Social Insurance, Sewerage and Solid Waste Management, Policing and Fire Departments and Public Welfare. Individual program totals were used in initial models and the final models used only the sum across all social programs.

Age-adjusted all-cause mortality at county level is taken from the US National Vital Statistics System (NVSS) accessed through the compressed mortality file of the Center for Disease Control and Prevention [38]. This contains detailed mortality data at county level across all 3,144 counties or county equivalents in the US. The compressed mortality data used in this analysis include mortality and population counts from 1968 to 2012 by cause of death (according to ICD 8,9 or 10 depending on year), state, county, age, race, sex and year. Demographic and economic variables at state and county level are from the US Census and the Interuniversity Consortium for Political and Social Research [39, 40]. These sources contain annual data at county level on race, education, income, poverty level, proportion urban and population by age used in this analysis. Data are available every year from 1790 to 2013 and relevant years' data were merged for 1972 to 2012, the years for which expenditure data is available. The dependent variable in this analysis was the Inter-County Concentration Index (ICCI) taken from Chapter 2 [1]. This has been calculated using mortality data from the US National Vital Statistics System and median income data from the US Census, both sources as described above. The calculation of the ICCI is described below.

The main sources of missingness were in the expenditure dataset. This data is self-reported by counties based on their own records [37]. At county level, there were 27,584 counties for which there were complete expenditure records, with 712 missing counties. The main source of missingness was from Alaskan counties, for which no data were collected between 1972 and 1982, accounting for 300 missing data points (75*4). Missing counties were tested for association with other variables in the dataset, and mapped to check for any spatial patterns (see Figures 4.5 and 4.6), but no such associations were found. Mortality data was available for all counties in all time years. Counties for which there are 20 deaths or fewer in a year are censored from that year of reporting. Other than this reporting is complete and of high quality. Mortality data are collected by state registries and demographic data and cause of death is taken from death certificates. All deaths are captured and denominators are from population Census estimates. Full details of the US Census sample sizes and data quality by year and definition are available from the website http://www.census.gov/acs/www/methodology/sample-size-and-data-quality/. Mortality rates are calculated by place of residence including total US, Census region, Census division, State and County [38]. There were no missing counties in demographic and economic datasets.

Statistical model of the effect of state-to-local transfers on ICCI

The primary dependent variable is the Inter-County Concentration Index (ICCI) described in Chapter 2 [1]. This is an innovative measure of mortality inequality between counties within each US state. ICCIs are calculated similarly to individual concentration indices by ranking counties by median income and measuring the cumulative proportion of mortality associated with each rank. The ICCI for each state in each year was derived from the regression formula:

$$2\sigma_r^2\left(\frac{h_i}{\mu}\right) = \beta_0 + \beta_1 r_i + \beta_2 X_i^T + \epsilon_i \qquad (1)$$

where (-1)*$\beta_1$is the estimate of the ICCI, β_0 is a constant, h_i is the county mortality rate, μ is the mean mortality for the state, r_i is the relative rank of county i in terms of median income, σ_r^2 is the variance of the relative rank, X_i^T is a vector of controls, β_2 is a vector of corresponding coefficients and ϵ_i is a county-specific error term. This approach to health equity measurement was first applied by Wagstaff, vanDoorslaer and Paci and further developed by Kakwani and colleagues [41, 42, 43]. Mortality has an inverse relationship with income so a negative ICCI represents inequity favoring higher income counties. For simplicity of interpretation, the dependent variable used in this analysis is the inverse value, so increasing inequity becomes more positive rather than more negative. Note that the absolute value is not used as there are a small number of positive values where inequity favors the poor counties.

The primary independent variable of interest is the aggregate level of state-to-local intergovernmental transfers (SLTs). As described in the conceptual framework, this is the main channel through which state governments can redistribute resources between counties and potentially affect levels of social inequality. This measure includes all state transfers for public expenditure at county level and is not disaggregated between spending categories. A second spending variable used in the analysis was total social spending at county level, summed across the state. Along with a county's total financial transfers in, this can be seen in the conceptual model as having a role in defining the level of public health and other amenities at county level. Both variables were calculated as the total of each category at county level, summed across the entire state. While there is considerable variation within states, there are enough differences between states and between years for these variables to generate meaningful results.

Several other spending variables were initially included in the model to identify the effects of program expenditures, however these were excluded from the final analysis due to high levels of collinearity which could produce biased estimates of their coefficients. To reduce the number of collinear variables, only two spending variables were used, SLTs and total county-level spending. Population clearly affects all spending and tax variables so models were tested using per capita spending as well as total spending and adjusting for population as a covariate. Urban and rural areas have different patterns of spending, even after accounting for population, so a measure of urbanicity was included as a covariate.

Statistical Analysis

There are a number of reasons that ordinary least squares (OLS) estimation may lead to biased estimates of the effects of SLTs and spending variables. There is a risk of bias in results due to endogeneity, or a correlation between the explanatory variables and the error term. This may be due to unobserved variables that affect both ICCIs and SLTs but cannot be included in the model (omitted variable bias).

State-specific trends may exist which, if strong enough, could result in seemingly significant patterns of association between inequity and transfers where none exist. Factors unrelated to SLTs or local expenditures may affect ICCIs, for example changing weather patterns causing major drought or flooding within some parts of a state. Global time trends are controlled for using a dummy variable for year and state-specific trends are investigated using state dummies and interaction between time and state.

State fixed effects may exist, due to unobserved factors, if some states have sustained high levels of inequity and high levels of transfers or vice versa. This could happen due to historical, cultural or environmental characteristics specific to a state, or policies implemented over the same period but not captured in the model. Time invariant effects of unobserved factors can be removed without explicitly including them in the model by using a specification which is based upon first differences or average differences. This removes the time-invariant influences at state level while retaining other variability and hence other associations can still be detected. Fixed effects models assume that unobserved variables are associated with observed variables whereas random effects assume there is no association over time.

OLS, Random Effects (RE) and Fixed Effects (FE) models were tested. Models with state level effects were preferred as Hausman specification tests compared random and fixed effects specifications and p-values are shown in Tables 4.2, 4.3 and 4.4 [44]. These showed random effects estimates to be inconsistent in most model specifications, so fixed effects specifications were preferred. Dummy variables for year, region and region/year interaction were included to adjust results for year-, region- and state-effects and the interactions between year and state.

To protect against multicollinearity, specifications of the model were tested, beginning with a basic model including SLTs and population and incrementally adding spending and demographic variables to the model to observe the robustness of coefficients of interest to the presence and absence of potentially collinear variables. The biggest risks were around the spending variables, which tended to be highly collinear at county level. Including more than one program area, for example hospital and non-hospital spending, policing, waste management, led to the loss in significance of others due to collinearity, so a breakdown by program area was not included. Final specifications included both SLTs and total county-level social expenditure variable described above. Despite some collinearity, both variables remained significant across most specifications and the specifications including both spending variables were preferred for the final model.

Reverse causation may occur as policymakers adjust SLTs to allow for an increase in ICCI in the same year. For example a natural disaster in the Appalachian counties of Kentucky, which tend to be poor and have high mortality rates, would result in increased ICCIs which could lead to state transfers to those county governments in response. To mitigate against the risk of reverse causality, the model was tested using a lag between SLTs and ICCIs. Lags of 1 to 5 years were tested, but the effect size decreased in size and significance with increasing lags and the main model is based upon a 1 year lag.

Based on these exploratory analyses, panel models with fixed effects were fitted to measure association between spending variables and concentration indices at state level. The main model was of the form:

$$C_{it} = \alpha_t + SLT_{it-1}\beta_1 + X_{it}\beta_2 + S_i + \varepsilon_{it} \qquad (2)$$

Where C_{it} is the ICCI measure of inter-county mortality in state i at time t, T is the total state-to-county transfer, X is a vector of control variables, S is a state-level fixed effect and α is a time dummy.

Dynamic panel bias, also known as Nickell bias, may arise in panel models with a small number of time points [45]. This bias is due to the correlation between the explanatory variable and the error created by the subtracting of mean values from individual values of explanatory and dependent variables. Dynamic panel estimators using generalized methods of moments approaches, such as the Arellano-Bond and Holtz-Eakin Newey and Rosen estimators [46] can be used to generate instrumental variables from lags of explanatory variables to infer unbiased estimates. The Arrelano-Bond estimation approach was tested, however tests of validity of the instruments generated failed (Sargan and Hansen tests) so these models could not be used and this risk remains as a limitation of the analysis.

Analysis is based on a long panel of data from 1972 to 2012 therefore there is a risk of serial correlation, through which observations in individual states are correlated with their own previous values, obscuring the effects of other variables. Serial correlation does not bias estimates but results in underestimates of standard errors and inflation of statistical significance. Serial correlation is found to be significant in all model specifications and several approaches to estimating standard errors were compared. Clustered robust standard errors were used in the final analysis as these were consistent with other approaches and provided the most prudent estimates of standard errors. The Appendix "Testing for Serial

Correlation" describes in detail the approach taken to identifying and addressing serial correlation in the models.

Results

The analytic sample contained an average of 3,056 counties across 47 states over 9 time periods from 1972 to 2012. Delaware, Rhode Island and Hawai'i have too few counties to construct a valid Inter-County Concentration Index (ICCI). Alaska has been included although the expenditure panel data only contains values from 1992. Statistics for some important variables in the analytic sample have been summarized in Table 4.1.

There is considerable variation between states for almost all indicators. Texas has by far the greatest number of counties, at 254. Los Angeles county has over 10 million inhabitants and California almost 38 million. There is, as would be expected, correlation between population and total state to local transfers so analyses were carried out using total and per capita SLTs. Specifications for the primary analysis use total amounts and control for population. Specifications using per capita amounts were analyzed for consistency but not reported as their estimates may suffer from ratio bias. The percentage of mortality that would have to be redistributed from the richer half of the population of counties to the poorer half to achieve a concentration index of zero is the ICCI multiplied by 75 [47]. This is the interpretation measure applied throughout this analysis.

To understand the spatial distribution of high and low income and mortality counties, which determine ICCIs, we first looked at the distribution of these counties. Figure 4.2

highlights these 'extreme' counties in a scatter plot of mortality against median income. Extreme counties in this sense are defined as those with the highest level of mortality and the lowest levels of income, or those with the lowest levels of mortality and the highest income. Dummy variables were created for counties in the top two mortality quintiles and bottom two income quintiles were grouped as "Sick and Poor" and the subset of these in the highest quintile mortality and lowest median income quintile were dubbed "Sickest and Poorest". Counties in the bottom mortality quintile and top median income quintile were labelled "Healthy and Rich". All other counties are labelled as "Not Extreme". Figure 4.3 illustrates the extreme counties cross-sectionally in a choropleth map for 2012. There is visible clustering in the South and extreme pockets in the Dakotas. Kentucky has a clear divide between the eastern Appalachian region and the rest of the state. The drivers for overall ICCI inequity vary by states, for example in California the urban coastal region is largely higher-income and lower mortality. In contrast, Mississippi has a lower ICCI since almost all counties in the state fall into one of the two poor/sick categories. The distribution of these counties bear striking resemblance to the maps of cardiovascular deaths and recently produced by Dwyer-Lindgren and colleagues which is not surprising given the significant geospatial inequities in mortality based on income found in Chapter 2 [1, 11].

This analysis is concerned with whether SLTs redistribute mortality geospatially in a more equitable manner. This would require some level of redistribution of resources to favor lower-income and higher mortality counties. The map of state-to-county transfers for the same year, shown in Figure 4.4, does not clearly correlate with the extreme counties cross-sectionally. These patterns are distorted by extremely high and low population counties, and the 41 counties with the highest per capita SLTs have been truncated at three standard deviations above the mean. These maps give a cross-sectional snapshot and cannot indicate any causality, however interesting patterns emerge when comparing Figures 4.3 and 4.4. Within states there appears to be some correlation with the higher mortality, lower income counties eastern California eastern Kentucky, parts of South Dakota and northern Louisiana showing concentrations of SLTs. In states with lower ICCI such as New York and Minnesota, the northern areas with relatively poor indictors receive greater per capita SLTs. Population is clearly important in these maps, as lightly populated areas get relatively higher per capita SLTs. Variables for population and urbanicity were included in the analysis to control for these effects.

Results from panel models support the hypothesis that state transfers reduce mortality inequalities across states in the US, with small but significant effect size. The primary results, using the preferred model specifications, are shown in Table 4.2. Alternative model specifications including varying combinations of demographic variables, both OLS and with state fixed effects, are shown in Tables 4.3 and 4.4. Table 4.3 details these results using SCTs as the only spending variable, and Table 4.4 also includes the sum of all county expenditures on social programs. To interpret the coefficient -0.0176 of state-to-local transfers shown in Table 4.2, we predicted the change in ICCI for a 10% increase in state-to-local transfers. Based on this we estimate that on average an increase of 10% in state-to-local transfers would on average lead to a reduction in ICCI of 4.2% on average. Ordinary least squares regression gave a similar pattern of results across model specifications and significant but smaller effects of state to county transfers, seen in Tables

4.2, 4.3 and 4.4. Results were robust to a range of specifications, as described in the Methods section, showing that SLTs had a significant effect on ICCI across OLS, Fixed Effects and Random Effects, including dummy variables for regions and years, and their interactions, as can be seen in Tables 4.2-4.5. OLS and FE specifications produced consistent estimates, with FE having larger effect sizes. Larger FE effect sizes across all specifications suggests that state-level effects are obscuring some of the effects of SCTs in OLS regressions.

Totals of county-level expenditures for social expenditures were significant in almost all model specifications and its effect in all cases showed a positive association with ICCI, suggesting that individual county spending works to increase health inequities rather than reduce them. Total population was significant in some analyses and the proportion of the population that is African American was significant in almost most specifications. This association was negative, so the direction of this effect was to associate a larger proportion of African American population at state level with a lower degree of inequity.

To break down results over the long time period, several sub-panels were created and the core models were re-run over these periods. Again, the significance of SLT coefficients was robust to time variation except in the earliest time period 1972 to 1987. However there were far fewer observations available for this period, so the smaller sample size may have affected the power of estimates. Table 4.5 shows period by period results for three non-overlapping time periods. Estimates by geographic region were generated but these were each based on a very small number of states (8 to 15 states) which was insufficient to produce valid estimates.

Discussion

This analysis finds statistically significant effects of SLTs on inter-county mortality inequities at state level. The effect size is small, with a 10% increase in total transfers resulting in a reduction in ICCI of only 4%. However this effect is robustly statistically significant across most model specifications tested, both including and omitting other spending variables, and may offer the potential to have a greater effect if it is actively used for this purpose. If the reduction of inequities between counties is seen as an important goal, these transfers could be designed more strategically to achieve improvements in equity. The SLT variable aggregates transfers across all programs and it is likely that some of these are responsible for the effect more than others. If such disaggregation becomes available in the future it may be possible to isolate a greater effect from certain categories of transfer, for example public health transfers.

Local government spending was also significant across most model specifications, with greater spending associated with higher inequity. Local governments' incentives are to improve health indicators among their own constituents. We see that spending on public health and non-hospital healthcare can reduce county mortality. Therefore counties with a higher income population and hence a higher tax base can afford to improve health in their counties more than counties with poorer populations. The positive association between total county spending and ICCI may be consistent with this, as a cycle of low income and high mortality and vice versa lead to diverging experiences between counties. Individual counties cannot be expected to concern themselves with health outcomes beyond their geospatial boundaries. However, this variable is aggregated across all counties in the model so it does not measure the association at county level. Another covariate that was significant in several model specifications was the proportion of population that is African American, with greater proportion being associated with lower inequity. Several states with among the highest African American populations, including Mississippi, Alabama, Tennessee and Arkansas, have low ICCIs due to almost uniformly poor indicators across counties, which may be driving this effect. Further decomposition of the role of race in geospatial inequity would require more granular data to disaggregate the population by race and other characteristics.

State governments' constituencies, however, cross these county lines and therefore they can have a role in equalizing outcomes, if that is their intent. The literature on fiscal decentralization theoretically predicts and empirically demonstrates health improvements from shifting resources to local levels [26, 27, 28, 48]. This is attributed in most models to the greater information of local governments about their communities, therefore counties can tailor their spending to their population's preferences and states move resources to close to beneficiaries to be most effective. An alternative driver is Tiebout sorting through which individuals self-sort to communities based on preferences (for health amenities in this case) and ability to pay. These effects should work in the same direction, as Oates stated "Even in the absence of mobility, the efficient provision of a local public good will be determined by the condition that the sum of the marginal rates of substitution equals the marginal cost, a condition that will usually differ among jurisdictions" [27, 49].

Given the geospatial inequities that exist and the equity-blind objectives of county governments (blind to ICCI, though not to within-county equity), the oversight role of the state is an important one. The identification of effective redistribution policies at state level has the potential to improve geospatial equity within their jurisdictions. If more transfers mean improved equity, perhaps poorer counties are using these additional resources more effectively towards improving mortality rates. A recent study by Bishai and colleagues [22] used vector autoregression methods to identify a causal effect of county level public health spending on county mortality. However the effect was context-specific, with extremely cost-effective years of life saved in some states and null or negative effects in others. Without more granular study of state- and county- specific programs we can only conclude that context matters and the effectiveness of county spending in reducing mortality varies by county and state.

These results are consistent with the literature, despite there being no directly comparable studies. Currie and Schwandt analyzed inequalities between county mortality, however they group counties by income level regardless of their location, hence grouping east and west coast cities together and grouping Appalachia with parts of Louisiana and Mississippi, which misses out on the role of the state, which is a primary concern of this analysis [4]. An important finding of Chetty and colleagues as part of the Health Inequalities Project is a geospatial finding that poor people have better life expectancy relative to the rich in wealthy areas than they do in poor areas [2]. While the reasons for this are not well understood, it holds out as a potential solution to reducing life expectancy inequities the diversion of resources to lower income areas. State transfers would be one channel through which this could be accomplished.

The relative advantages of state policymakers focusing on geospatial inequity compared with other perspectives of equity is up for debate, and have been discussed in related work (Chapter 2). However this additional perspective on equity has had little emphasis in the literature, and one need only look at county-specific mortality maps and in Figure 4.3 to realize that geospatial inequalities are at least part of the overall equity picture in the US [11]. Hotspots of poverty coincide with mortality from multiple causes in the Mississippi Valley, Native American reservations in the Dakotas, and large swathes of the Appalachian mountains. Geospatial measurement of health inequities and policies to reduce them provide a tool for policymakers and researchers to consider this perspective alongside more traditional measures.

Limitations

There are several important limitations to this analysis. The control variables here are aggregated at state level and disguise a lot of heterogeneity at county level and below. A previous analysis (Chapter 2) investigates some of this variability by decomposing the ICCI using county level controls. Ideally a multi-level model would be implemented using individual-level data and constructing geospatial hierarchies to group individuals but this data was not available at the time of analysis. There are only 47 states that have a sufficient number of counties to be used in the analysis, which is not a enough large panel to stratify the analysis beyond a basic level. It is almost certain there are unobserved variables that affect inter-county inequity and are associated with the error term in our model. It is also possible that reserve causality exists wherein higher levels of inequity lead to increased transfers, for example a localized natural disaster. Fixed and random effects models were implemented to control for time-invariant state level unobservables and a time lag was introduced to reduce the risk of reverse-causality. We were also limited in the type of spending variables that are available at county level. If in future state-to-local transfers could be disaggregated based on their specific use, ie. public health, waste disposal, policing, clearer effects could be measured. Spending variables at local level are self-reported so there may be errors or inconsistencies over time that could distort findings, although this would affect categories of spending much more than aggregate transfers.

If individual characteristics such as race and income are significant, which they appear to be, the aggregation of these measures at state and county level could obscure effects upon subpopoulations. Individual level data would allow a study of the effects of spending on individual survival and the role of race, urban or rural domicile as well as individual income. This ecological bias is a major limitation of this analysis.

Apart from data limitations, the statistical methods do not fully allow for all the risks described in the methods section. It is almost certain that some endogeneity remains in the model, since the relationships between variables are extremely complex and there is insufficient data to stratify by more than a few variables. Using fixed effects to difference out effects from unobserved variables is limited as it assumes that their association with modelled variables does not change over space and time. This is a difficult assumption to confirm and in such a complex system it is likely to be a source of error. A number of confounding variables were included in a range of specifications, however these represent state-level demographic proportions and are a crude way to adjust for the myriad interactions of race, income and other health and equity related factors. A survival model based on individual characteristics would adjust for these factors in a more sophisticated manner. Dynamic panel bias remains a risk since the Arellano-Bond approach failed to produce a valid estimator. The direction of these biases is unknown, although we have argued in the discussion that our fixed effects estimates probably underestimate effect size. The robustness of the effects to model specification and stratification strengthens our results however, given these methodological limitations, it is not possible to assign a causal relationship to the association we find.

Conclusions

We have shown that state-to-county transfer payments are negatively associated with inter-county mortality inequity by a small but statistically significant amount. The patterns of mortality and income at county level reveal geospatial inequities across the US as a whole and within states. The conceptual framework described here proposes local and state spending as a channel through which inequities can be reduced. Local governments can tailor their spending to their populations and provide public health and related public amenities to improve health at county level. However their ability to provide these amenities is based upon their tax base and hence the incomes of their populations. This has the potential to become a vicious cycle in widening health disparities associated with income levels. State transfers provide one possible way of re-balancing resources and improving the capabilities of counties with poorer populations to improve their population's health relative to their neighboring counties.

Geospatial inequity should not be considered in isolation. Policies can be targeted to reduce inequities from multiple perspectives and much research has been focused on targeting racial and income-based inequities as well as overall population burden of mortality [50]. This analysis builds on that literature by providing a link between policymakers and measures of geospatial equity, demonstrating that by redistributing resources through intergovernmental transfers states can reduce unfair health inequalities between their constituent counties.

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Table 4.1: Descriptive statistics from the analytic sample in 2012

Statistic at state level	Mean	SD	Median	Min	Max
Number of counties per state	69	45	68	9	254
Population (million) per county	6.6	7.1	4.7	0.6	37.9
Per capita state-to-county transfers (000)	1.79	0.55	1.17	1.2	3.8
Health Inequity (% of mortality to be redistributed to achieve equity)	3.0%	1.5%	1.5%	0.8%	6.8%

Table 4.2: Fixed Effects Regression of State ICCIs on State-to-County Transfers including Total County Spending and time and region dummies 1972-2012

	OLS	FE	OLS	FE
State-to-county transfers (log)	-0.00591 [0.00403]	-0.0176** [0.00736]	-0.00914* [0.00467]	-0.0135* [0.00677]
Sum of all local government spending (log)	0.00473 [0.00704]	0.0335** [0.0128]	0.00774 [0.00790]	0.0365** [0.0136]
Population (log)	0.00108 [0.00575]	-0.0264 [0.0181]	0.00156 [0.00618]	-0.0442** [0.0185]
Proportion of population with at least a high school education	-0.00375 [0.0232]	-0.0848 [0.0547]	-0.0264 [0.0320]	-0.0600 [0.0660]
Proportion of civilian workforce that is employed	0.0333 [0.0618]	0.142 [0.106]	0.122 [0.0748]	0.120 [0.121]
Proportion of population that is African-American	0.0197 [0.0125]	-0.248** [0.0974]	0.0302** [0.0149]	-0.134 [0.0874]
Dummy variables for the interaction of State and Year included			X	X
Dummy variables for each Year included	X	X		
Constant	-0.00880 [0.0667]	-0.0235 [0.161]	-0.0811 [0.0766]	0.0994 [0.197]
Observations	419	419	419	419
R-squared	0.271	0.464	0.310	0.503
Number of statefip		47		47
Hausman test (p-value)		0.0197		0.0164
Woolridge test for serial correlation (p-value)		0		0

Table 4.3: OLS and Fixed Effects Regression of State ICCIs on State-to-County Transfers including Total County Spending 1972-2012

	Specification 1		Specification 2		Specification 3	
	OLS	**FE**	**OLS**	**FE**	**OLS**	**FE**
State-to-county transfers (log)	-0.0112*** [0.00349]	-0.0194*** [0.00493]	-0.00981*** [0.00362]	-0.0164*** [0.00471]	-0.0101*** [0.00362]	-0.0163*** [0.00462]
Population (log)	0.00476 [0.00442]	-0.00751 [0.0145]	-0.00315 [0.00550]	-0.0268 [0.0211]	-0.00237 [0.00557]	-0.0284 [0.0186]
Proportion of population with at least a high school education			-0.0648*** [0.0226]	-0.113*** [0.0396]	-0.0372* [0.0202]	-0.106*** [0.0352]
Proportion of civilian workforce that is employed			0.0592 [0.0435]	0.0335 [0.0387]	0.0326 [0.0436]	0.0390 [0.0403]
Proportion of population living in urban areas			0.0297*** [0.00937]	0.00380 [0.0224]		
Proportion of population that is African-American			0.0100 [0.0124]	-0.272** [0.103]	0.00675 [0.0118]	-0.275** [0.109]
Proportion of population that is Hispanic			0.00310 [0.0125]	-0.0269 [0.0697]		
Year	0.000762*** [8.48e-05]	0.000749*** [0.000155]	0.00118*** [0.000170]	0.00167*** [0.000417]	0.000976*** [0.000149]	0.00160*** [0.000297]
Sum of all local government spending (log)	0.00730 [0.00555]	0.0222** [0.00843]	0.00943 [0.00643]	0.0304** [0.0124]	0.0121* [0.00648]	0.0299** [0.0129]
Number of observations	419	419	419	419	419	419
R^2	0.239	0.396	0.280	0.453	0.252	0.453
Number of states		47		47		47
Hausman test (p-value)		0.3654		0.0141		0.0039
Woolridge test for serial correlation (p-value)		0		0		0

Table 4.4: OLS and Fixed Effects Regression of State ICCIs on State-to-County Transfers omitting Total County Spending 1972-2012

	Specification 1		**Specification 2**		**Specification 3**	
	OLS	**FE**	**OLS**	**FE**	**OLS**	**FE**
State-to-county transfers (log)	-0.00812*** [0.00259]	-0.0141*** [0.00480]	-0.00649** [0.00283]	-0.0128** [0.00491]	-0.00589** [0.00283]	-0.0128** [0.00483]
Population (log)	0.00920*** [0.00285]	0.00819 [0.0117]	0.00329 [0.00331]	-7.29e-05 [0.0154]	0.00612* [0.00321]	-0.000599 [0.0114]
Proportion of population with at least a high school education			-0.0548** [0.0216]	-0.0724* [0.0371]	-0.0217 [0.0184]	-0.0706** [0.0291]
Proportion of civilian workforce that is employed			0.0763* [0.0420]	0.0970*** [0.0296]	0.0539 [0.0422]	0.0977*** [0.0280]
Proportion of population living in urban areas			0.0314*** [0.00931]	0.00574 [0.0226]		
Proportion of population that is African-American			0.0132 [0.0122]	-0.331*** [0.104]	0.0112 [0.0116]	-0.330*** [0.108]
Proportion of population that is Hispanic			0.00196 [0.0125]	-0.00889 [0.0748]		
Year	0.000808*** [7.72e-05]	0.000981*** [0.000140]	0.00118*** [0.000170]	0.00174*** [0.000425]	0.000958*** [0.000149]	0.00173*** [0.000307]
Sum of all local government spending (log)						
Number of observations	419	419	419	419	419	419
R^2	0.236	0.379	0.276	0.432	0.246	0.432
Number of states		47		47		47
Hausman test (p-value)		0.3091		0.0036		0.0004
Woolridge test for serial correlation (p-value)		0		0		0

Table 4.5: Fixed Effects Regression of State ICCIs on State-to-County Transfers including Total County Spending for sub-periods between 1972 and 2012

	1972 to 1987	1987 to 2002	1997 to 2012
State-to-county transfers (log)	-0.00320 [0.00589]	-0.0228** [0.00945]	-0.0306** [0.0135]
Sum of all local government spending (log)	0.0485*** [0.0167]	0.0243 [0.0152]	0.0468*** [0.0158]
Population (log)	-0.110*** [0.0396]	0.0256 [0.0305]	-0.0188 [0.0205]
Proportion of population with at least a high school education	-0.0167 [0.0784]	-0.0780 [0.0594]	-0.364* [0.197]
Proportion of civilian workforce that is employed	0.131 [0.114]	0.110 [0.168]	0.132 [0.148]
Proportion of population that is African-American	-0.353 [0.228]	-0.121 [0.218]	-0.348 [0.254]
Year	0.000309 [0.000809]	0.00104* [0.000618]	0.00315** [0.00147]
Constant	-0.0506 [1.575]	-2.523** [0.979]	-6.158** [2.862]
Observations	184	187	188
R-squared	0.270	0.339	0.347
Number of statefip	46	47	47

Figure 4.1: The role of State-to-Local Transfers in geospatial health equity

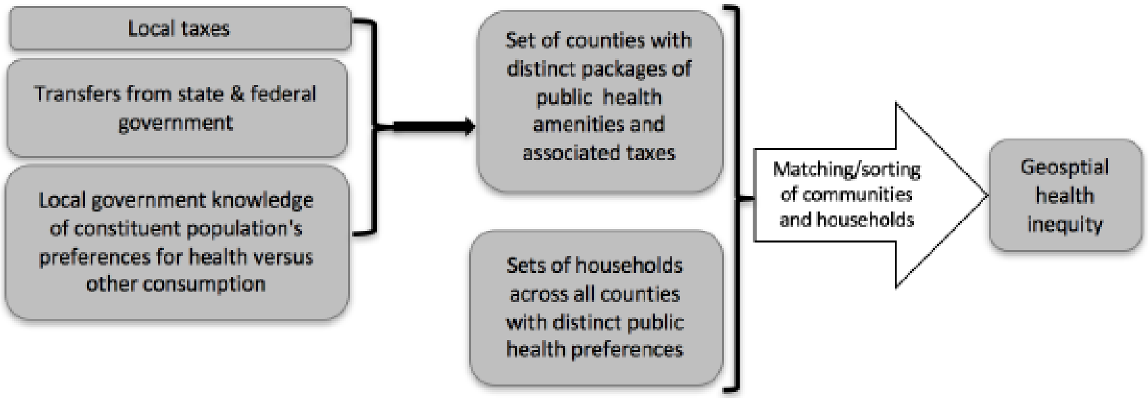


Figure 4.2: Scatter Plot of county mortality rates against median income in 2012 highlighting extreme counties

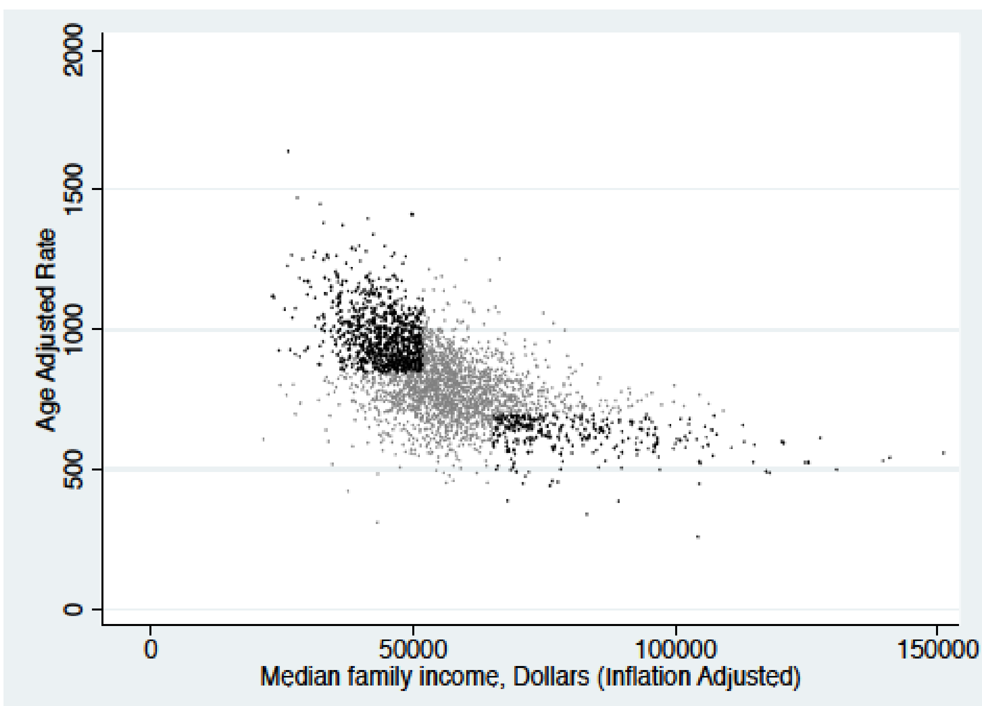
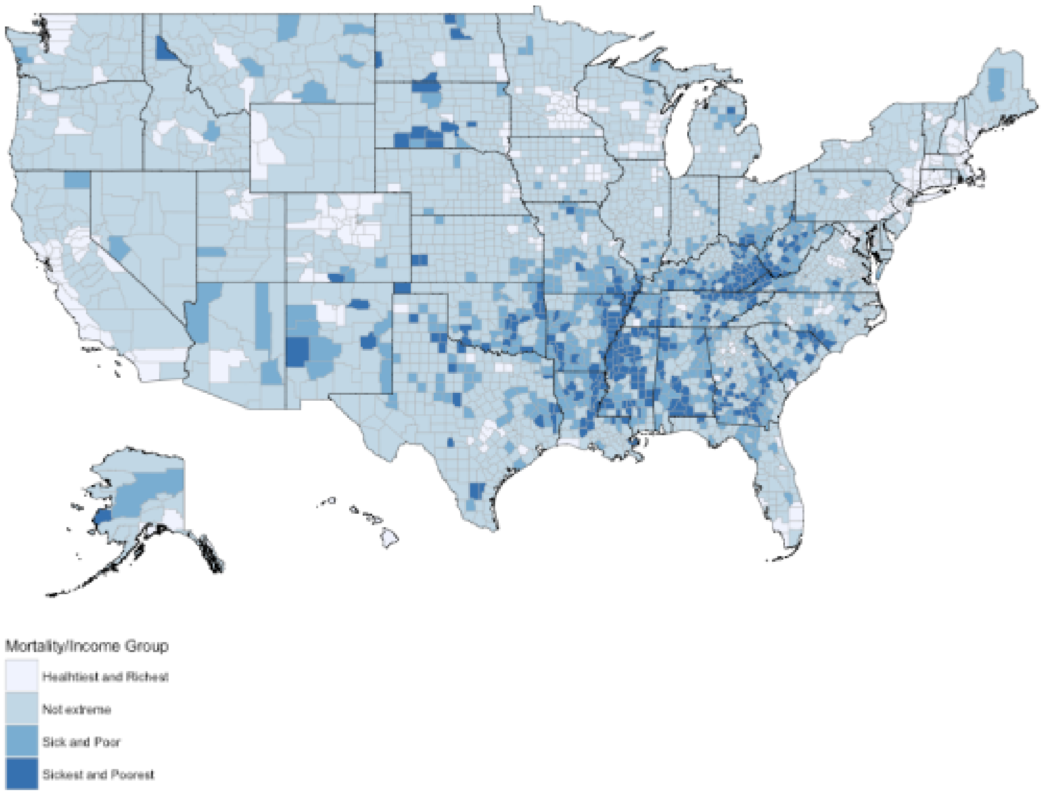


Figure 4.3: Map of extreme Mortality/Income Counties in 2012



Source: US Census and CDC Compressed Mortality File

Figure 4.4: Map of State-to-Local Transfers per capita by county in 2012

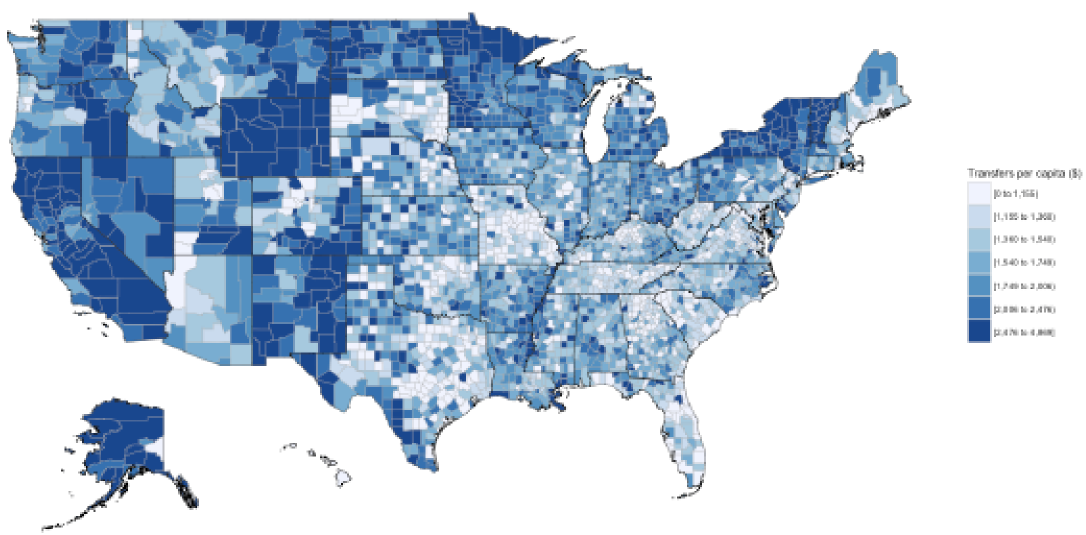


Figure 4.5: Counties with missing expenditure variables in 1972

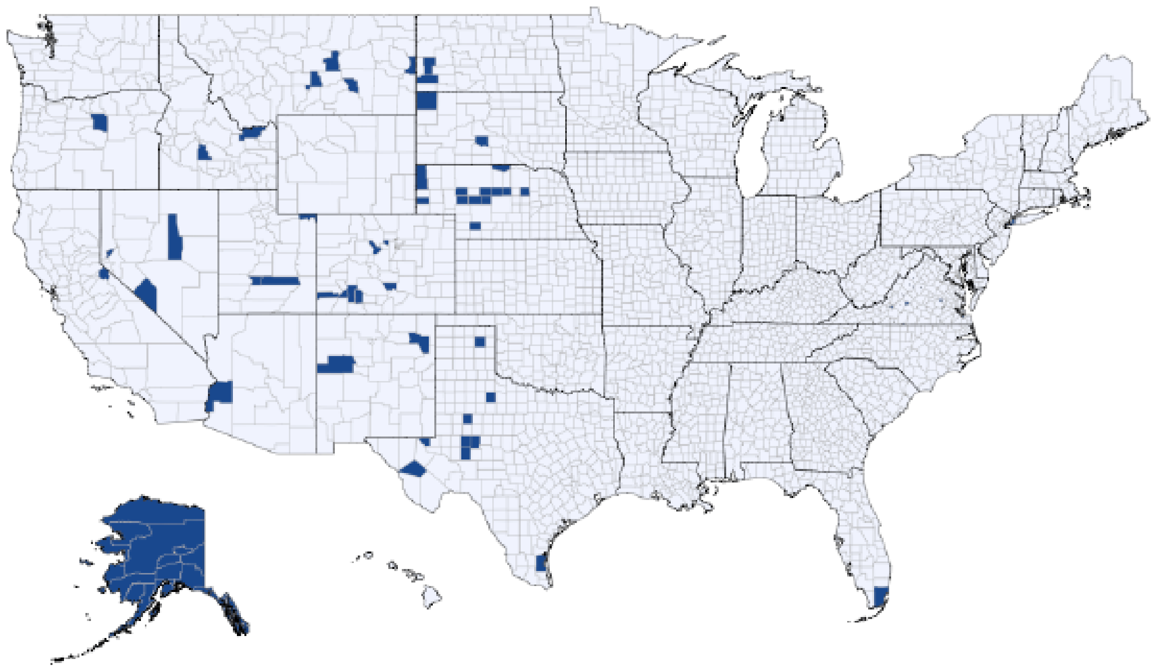
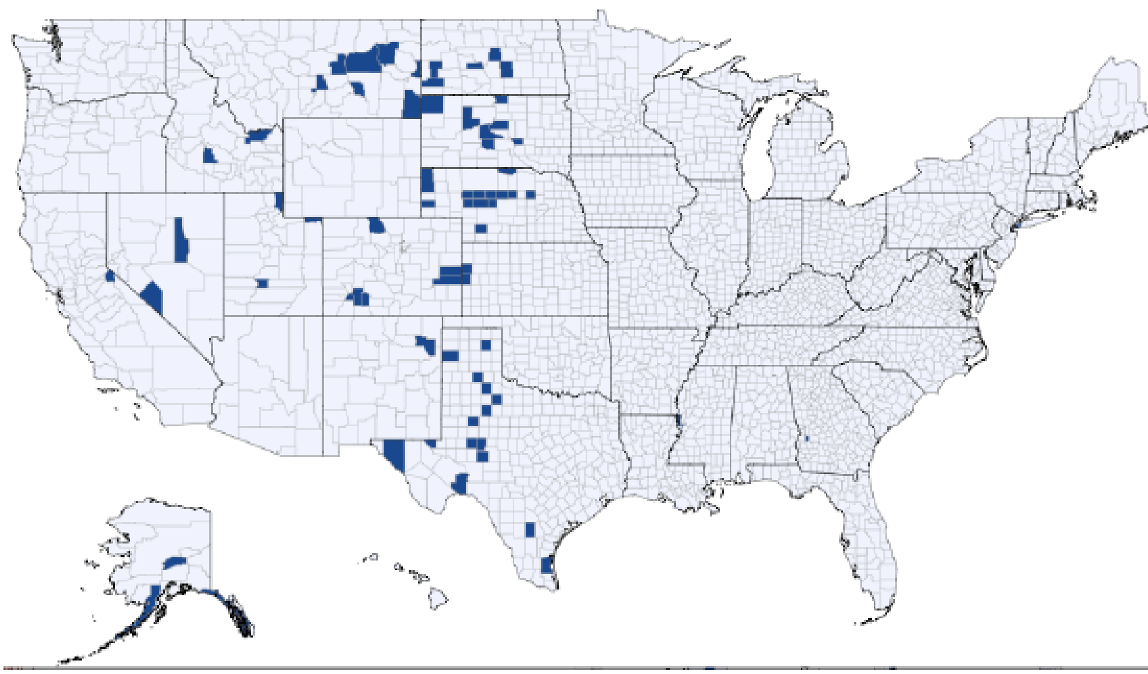


Figure 4.6: Counties with missing expenditure variables in 2012



Chapter 5: Conclusions

Overview

Geospatial health inequities, across US county mortality rates and child mortality rates in India, have been shown to be significant and growing over the periods of analysis. The distribution of health has been shown to reflect the distribution in the income or wealth of counties' or districts' population. This highlights the role of local and state governments in the health of their populations and the public health imperative to target health amenities and interventions geospatially as well as based on income- or race- defined populations. These results demonstrate that geospatial measures can be used to enhance our understanding of health equity and to address the roots of such inequities through local governments.

Geospatial health inequity exists and is measurably significant and increasing. Wealthy counties and districts have better population health than poorer ones. This is counter to social justice principles including Rawls' Difference Principle, that social and economic inequalities should benefit the least-advantaged in society most [1, 2]. In an extension of the Matthew Effect, healthy and rich places are becoming more healthy, and poor and sick places are becoming more sick [3]. This is consistent with the cycle of geospatial inequity proposed in this thesis, and represents a facet of distributional injustice that is not sufficiently addressed in the existing literature of individual income and racial inequities. As discussed in the analyses, the stratification of health by place can increase stress and has psychological health implications for disadvantaged populations with frequent exposure to better off communities. Differing life expectancies by place can result in unjust fiscal subsidies of old-age benefit programs by shorter-lived, poorer populations.

It can be measured in a consistent way in various contexts. The first step in addressing such inequity is to measure it, and the methods that have been described here produce consistent results in different contexts. They have been shown to be robust to decomposition and stratification and respond in ways that are logical and consistent with the literature. Now they can be used to monitor geospatial inequities and hold policymakers accountable for their mitigation.

Trends and patterns in these measures reflect the interplay of politics, economics, policies and migration. Local governments have the potential to make efficient investments in their populations through information on their preferences and needs. They also provide a channel through which the wealthy can capture disproportionate benefits from those investments. In India, the growth of the private sector in healthcare combined with the economic migration of health workers has contributed to the geospatial concentration of child mortality. Urbanization and migration may be driven by economic opportunity but can affect health care access and access to health amenities of wealthier counties and districts. Measuring and interpreting inequities in terms of local and state government policies and borders can help to understand the complex interactions between these social, political and economic factors.

Local and state governments have policies available to them that make the distribution of health more just. This analysis has identified some forms of expenditure in the US context that can affect ICCI in one direction or the other. There are tools available to local and state governments that can be observed and their effects upon health equity measured. State and federal governments can be held to account by their constituents based on whether or not they choose to use these tools to achieve a more just distribution of health.

	Chapter 2 (Manuscript 1)	**Chapter 3 (Manuscript 2)**	**Chapter 4 (Manuscript 3)**
Sample	Approx. 3,000 US counties from 1972 to 2012	600 districts of India in 2001 and 2012 (555 districts in state-level analysis)	Panel of 47 US States at 5 year intervals from 1972 to 2012
Method	Inter-County Concentration Index (ICCI), a geospatial adaptation of the Concentration Index of Inequality, and corresponding Concentration Curves. Moran's I for spatial associations	Inter-District Concentration Index (ICCI), a geospatial adaptation of the Concentration Index of Inequality, and corresponding Concentration Curves. Moran's I for spatial associations	Fixed Effects and Ordinary Least Squares models.
Main question	Is mortality rate inequity across US counties statistically significant at national and state levels, and how has this changed over the period of analysis?	Is under-five mortality rate (U5MR) inequity across Indian districts statistically significant at national and state levels, and how has this changed over the period of analysis?	Are governmental expenditure variables State-to-local intergovernmental transfers and county level social spending associated with changes in ICCI over the period 1972 to 2012?
Main finding	ICCIs are statistically significant and there has been a significant upward trend over the period of analysis. Mortality inequity is robust to adjustment for demographic and economic covariates. At state level, all 47 states in the analysis had statistically significant inequity in 2012 and this had increased between 1972 and 2012 in all but seven states.	IDCIs are statistically significant and have increased significantly between 2001 and 2012. U5MR inequities are robust to urban-rural stratification and adjustment for demographic and economic covariates. At state level 16 out of 22 states had statistically significant U5MR inequity in 2012 and 11 out of 22 IDCIs had increased between 2001 and 2012.	State-to-local intergovernmental transfers are negatively associated with state ICCI and county level social spending is positively associated with state ICCI

Public Health and Research Implications

When taken together, the results of these analyses present a set of conclusions that add a geospatial perspective to the discussion of health equity in research and policy. In particular, geospatial health inequity is significant and represents a dimension of social injustice that has not been well recognized or prioritized. We now have a method of summarizing and tracking this inequity that can be used to hold policymakers accountable. These measures reflect political economies, local and state policies and provision of public amenities, and intra-country migration. These relationships need to be understood further. Finally, governments have policies available to them that can reduce geospatial inequities. Intergovernmental transfers can be used to redistribute health within a state and reduce disparities between counties.

These analyses complement one another in context and policy relevance. Chapter 2 presents and tests our measure of geospatial health equity in the context of good data, low overall mortality rates and a forty-year time period. Chapter 3 applies the method to an alternative health measure (U5MR) in a setting with higher mortality rates and less reliable data sources. These demonstrate the flexibility of the method to a wide range of contexts, indicators and data quality. Chapter 4 extends the use of the measure, illustrating its use it as a dependent variable to assess the effects of spending policies.

To fully understand the complexities of health equity a geospatial measure adds a significant perspective to existing income and race based measures. It brings to the fore the policy trade-off between efficiency and equity, the political economy of the capture of health and social interventions and expenditures and the insufficiency of DALYs in the measurement of population health. It also suggests resource redistribution through local government as a potential path to the reduction of mortality inequity in the US. These three applications illustrate the application of a geospatial perspective to health equity in very different contexts. They should be interpreted in the political and economic context within which they operate, and in conjunction with the absolute levels of health outcomes. For example, state-by-state analysis in the US reveals much higher inequity in California than Mississippi due to wealthy, low mortality coastal counties. At a federal level, equity may be best served by directing resources to Mississippi while California addresses its internal inequities. To understand the high geospatial inequities in India requires us to recognize characteristics of the labor market for health professionals and the shift from public provision of health services to private provision. As the country with the highest number of child deaths, the debate between absolute gains in child survival and how equitably they are realized is particularly relevant here.

Results have demonstrated that US states can reduce unfair health inequalities between their constituent counties through intergovernmental transfers. However the pathways through which these act are not clear at this level of analysis. Recent research has shown that county spending on public health and non-hospital healthcare is associated with significant increases in life expectancy in some states, while being ineffective or having the reverse effect in others [4]. Further research into the specific programs and types of spending that are most effective in reducing mortality inequities would build upon these results. Recent research in India has defined an intergovernmental transfers variable at state level, Redistributive Resource Transfers, as being equivalent to internal 'aid'. Their relationship with geographic advantages of some states and their effect on economic and governance indicators has been measured [5]. If similar data is made available at district level it would allow a study equivalent to that in Chapter 4 to be conducted on our India IDCIs. The results of these analyses should prompt a deeper look into geospatial health equity in the US, India and elsewhere. The types of analysis possible may be dependent on the availability of individual level data linked to location, which should be increasingly available given the growth of GPS-linkages in data collection. There are a range of more granular studies that could provide interesting insights to geospatial inequities. Historic, economic and racial divisions within cities, as well as cycles of deterioration and sometimes urban renewal could provide interesting variation. Individual level data would allow stratified analyses by cause of death and by subpopulations. Geospatial equity across subpopulations, for example African Americans in Mississippi versus those in New York city, may also be revealing in disaggregating geospatial, race and class effects on health. Chetty and colleagues find health behavior to be strongly associated with life expectancy inequalities. Such behaviors can be linked to local social norms and culture, all of which could be understood better through a geospatial perspective [6]. Geographic features that could lead to health advantages require further study and incorporation into geospatial models. For example, coastal areas in India have been identified as a source of economic and health advantages. Future analyses could build such environmental variables into models to decompose effects further.

Conclusion

Citizens globally are concerned with the inequalities that surround them and the social injustices that have arisen from the concentration of resources among the wealthiest. It is not so clear that they are aware of the glaring disparities within their own states and countries. This thesis provides a measure of geospatial inequities between counties in the US and districts in India and demonstrates that they are significant and increasing. The tangible and proximate nature of such inequities would be unacceptable to many, if a geospatial perspective is added to current understanding of health equity.

Policies exist that can address these injustices and distribute health more equitably. Local, state and federal governments have a role to play in redistribution of health by enacting such policies, given the role of income and wealth in concentrating health in some counties and districts. Geospatial measures of equity, including those proposed in these analyses, can be used to hold governments accountable for the continued existence of inequities in their jurisdictions.

The trends seen in ICCIs and IDCIs are not well understood by researchers. The role of urbanization and intra-country migration needs to be studied, to identify the main causes of the observed trends and to understand the interactions between social, political and economic factors on geospatial disparities and possible self-sorting by place.

Geospatial inequities are increasing. Rich counties and districts are getting more healthy and poor ones less healthy. Citizens can hold states responsible for breaking the cycle of inequity by targeting resources geospatially and lifting counties or districts with the poorest populations rather than aiming for average improvements in population health. If health is a human right, the increased concentration of health in the wealthiest places does not reflect a just society.

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Appendices

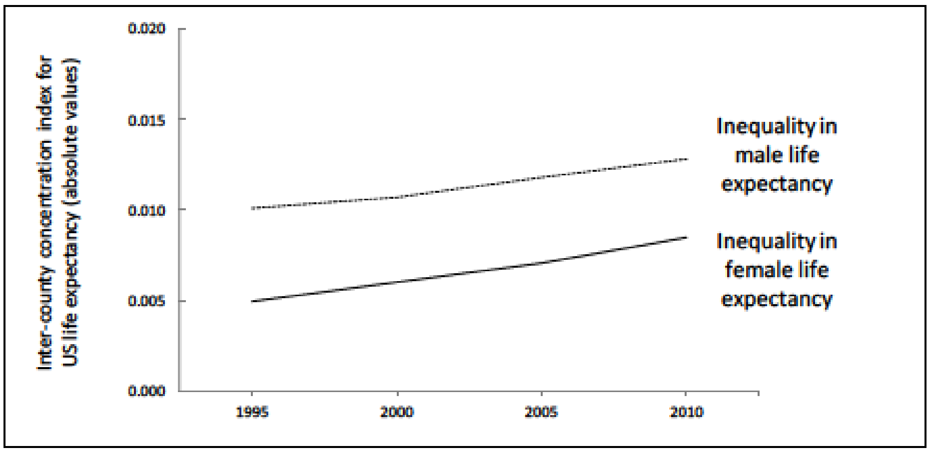
Appendix 2.1: Robustness checks of the Inter-County Concentration Index

Health inequity as measured by ICCI is consistent across measures. Table A2.1 compares inter-county inequalities calculated based upon two alternative approaches, the Slope Index of Inequality and the Coefficient of Variation, as described in the Methods section. Concentration indices and slope indices measure inequalities ranked by county median income and coefficient of variation measures the overall variability between mortality rates. While the measures are not on the same scale, all three measures indicate a large increase over the period, with each increasing over every five-year period. There is also clear consistency between the measures, with a correlation of 99% between ICCI and SII and 81% between ICCI and CV. Repeating the analysis at national level using life expectancies instead of age-adjusted mortality rates gives consistent results, as can be seen in Fig. A2.1. There is a notable difference between inequality measures for male and female populations, but both show a similar significant increase in life expectancy inequality during each five-year period from 1985 to 2010. The consistency between the results when comparing with methodologies used elsewhere in the literature provides some level of validation of the new version of the CI used here.

Table A2.1: Comparing measures of inter-county mortality inequality (Age-adjusted mortality rate), US 1972-2012

	1972	1977	1982	1987	1992	1997	2002	2007	2012
Concentration Index	-0.0167	-0.0174	-0.0162	-0.0206	-0.0299	-0.0402	-0.0449	-0.0577	-0.0609
Slope Index of Inequality	-125.30	-112.10	-96.57	-119.90	-166.60	-223.00	-244.90	-291.90	-303.10
Coefficient of Variation	0.1677	0.1374	0.1293	0.1417	0.1444	0.1614	0.1627	0.1778	0.1822

Figure A2.1: National inter-county mortality inequality for male and female life expectancy 1995-2010



Appendix 3.1: Testing the district wealth measure for robustness

We compared the effects of using district median wealth indices with district mean wealth indices as a robustness check. Household indices were calculated for each household and the median and mean wealth index for each district was using sample weights to assign district level values. In OLS regressions of district U5MR on median and mean wealth index, both were strongly significantly associated with district mortality rates for each time period. All model specifications for IDCI calculations were then compared across measures and times. Table A3.1 shows these results for the preferred model specification from Table 3.3 (column 5), comparing results between median and mean wealth indices for both 2001 and 2012.

While both measures are significant, the median wealth index has a larger effect size across all specifications. We repeated this comparison with an unweighted mean (setting all asset weights to 1) but this was not statistically significant except in a small number of model specifications. It is important to note, as Formula 3 details, the IDCI is based upon the rank of a district's wealth measure rather than the measure itself. The correlation between district rankings based upon mean and median wealth index was over 98%, so the choice of measure does not make a very large difference to district rank, or the resulting IDCI. Ranks are also not as sensitive to individual district variability, as variance of ranks (in equation 3) is smaller than variance of the wealth index overall. Therefore the stronger association found with median wealth index made this a preferred measure. In addition, median scores may be a more justifiable measure based on the distributions of asset scores being moderately skewed upwards. The upper tail for each district could be considered as a set of outliers which results in mean values that are higher than the median. The district median is closer to the household index for a greater proportion of households and can be considered more reflective of the typical wealth level of households in the district.

Weightings from recent literature based on the DLHS surveys [1] were used to develop household level indices for all households in DLHS-3. These were compared with household indices calculated using a similar method within DLHS-3 and found to correlate strongly, with a Pearson correlation coefficient of 93%. As a further check on the stability of median wealth index, the correlation between wealth indices in DLHS-2 and DLHS-3 was calculated as 84%, indicating a level of consistency over time.

Table A3.1: Comparison of the effects of Median and Mean District Wealth Index

		2012		2001	
		Median District Wealth Index	Mean District Wealth Index	Median District Wealth Index	Mean District Wealth Index
Ranking of District Wealth (Median or Mean)		-0.104*** [0.0166]	-0.0859*** [0.0174]	-0.0383*** [0.00817]	-0.0345*** [0.00873]
Population (million)		-4.118*** [1.219]	-2.968** [1.389]	-4.574*** [1.113]	-4.597*** [1.121]
Women's education level (Avg. number of years of education of mothers in the district)		-0.000117*** [1.99e-05]	-0.000147*** [2.30e-05]	-9.54e-05*** [1.80e-05]	-9.58e-05*** [1.82e-05]
Proportion of district households	Members of a scheduled caste	6.16e-05 [0.000243]	-0.000123 [0.000250]	0.000424** [0.000190]	0.000384** [0.000191]
	Members of a scheduled tribe	3.07e-05 [0.000133]	0.000212 [0.000162]	0.000401*** [0.000116]	0.000397*** [0.000117]
	Living in rural area	-0.000592*** [0.000121]	-0.000641*** [0.000145]	-0.000259** [0.000115]	-0.000262** [0.000116]
	Illiterate (head of household)	0.000444** [0.000219]	-1.02e-05 [0.000285]	0.000342 [0.000229]	0.000355 [0.000228]
	Employed last year (head of household)	-0.000510*** [0.000180]	-0.000331* [0.000196]	-0.000422** [0.000168]	-0.000436** [0.000169]
	No access to toilet	0.000143 [0.000160]	[0.0148] 0.000144	0.000288*** [0.000110]	0.000321*** [0.000110]
	With health insurance	0.000460 [0.000298]	0.000144 [0.000164]	4.20e-05 [0.000282]	5.33e-05 [0.000282]
South dummy		-0.0555*** [0.00548]	-0.0567*** [0.00538]	-0.0402*** [0.00387]	-0.0410*** [0.00391]
East dummy		-0.0363*** [0.00677]	-0.0356*** [0.00709]	-0.0270*** [0.00470]	-0.0269*** [0.00483]
West dummy		-0.0154** [0.00632]	-0.0219*** [0.00672]	-0.0124** [0.00540]	-0.0129** [0.00542]
Northeast dummy		0.0199* [0.0115]	0.0341** [0.0148]	-0.000478 [0.00835]	0.000295 [0.00842]
Number of districts		597	597	597	597
R^2		0.583	0.520	0.510	0.506

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Appendix 4.1: Testing for Serial Correlation

Panel data may contain serial correlation, through which individual observations are correlated with their values in previous time periods. This could result in underestimates of standard errors and inflation of statistical significance, though coefficient estimates will not be biased [1] We tested for serial correlation using the Breusch-Godfrey/Woolridge test for serial correlation in multiple panels [1] and p-values for these tests are reported in results tables 4.2, 4.3 and 4.4. These tests identified statistically significant serial correlation in almost all model specifications. In order to address this serial correlation and have confidence in the regression estimates, we tested models using several types of estimation and compared standard errors across methods.

The first step was to compare state panels using fixed effects models and a range of lag lengths to identify which provided the best fit to the data. Model fit was measured using the Akaike Information Criterion (AIC) and the best models were those at lag 1 across all specifications, ie. 1 time period equivalent to 5 years in our analysis. We then tested all specifications using cluster robust standard errors [2] with fixed effects, which are heteroscedasticity-robust but do not explicitly adjust for serial correlation.

Estimates using Driscoll-Kraay standard errors are recommended in the case of serial correlation and spatial correlation [3, 4]. This approach uses a nonparametric covariance estimator to produce standard errors that are heteroscedasticity consistent and robust to spatial and temporal dependence. We implemented these using the xtscc command in Stata [3]. We tested a range of specifications using moving averages at lags of 1, 2, 3, 4 and 5, with most exploration of various specifications at lag 1 which provided the best fit to the data. The effects of our primary independent variable of interest, lgTran, remained statistically significant at a level of 0.01 throughout. The size of standard errors vary by lag length, however all standards errors using this approach were lower than the Roger's cluster robust standard errors described above, across all specifications.

Table A4.1 shows a comparison of the preferred model specification across each approach, ie. comparing standard errors across OLS, FE, FE with Driscoll-Kraay and a lag length of 1, and FE with Roger's Cluster Robust standards errors, which were used for the final model. Note that all comparisons are made with model specification 3 in Table 4.3 since factor variables used in Table 4.2 are not permitted in the xtscc command for Driscoll Kraay errors.

These results are consistent with the literature. Hoechle ran Monte Carlo simulations to compare standard errors across methods and found that Driscoll-Kraay standard errors are "slightly less adequate than Rogers standard errors when spatial dependence is absent". In our previous analysis of these data (Brady, Paper 1) we conducted Moran's I tests of spatial correlation between states ICCIs and found no statistically significant spatial association. Driscoll-Kraay standard errors in our analysis were higher than those in OLS and FE models and lower than FE with Roger's cluster robust standard errors throughout. We decided that the most prudent solution to the serial correlation identified was to use Rogers robust standard errors, which are consistent with the serial-correlation robust standards errors and are in almost all specifications higher. Therefore this approach provides the most confidence that our conclusions of significant effects are not a function of the serial correlation in the data.

Table A4.1: Comparison of regression standard errors using alternative approaches to address serial correlation

	OLS	**FE**	**FE with Driscoll-Kray Standard Errors**	**FE with Cluster Robust (Roger's) Standard Errors**
State-to-county transfers (log)	-0.0101*** [0.00362]	-0.0163*** [0.00366]	-0.0163*** [0.00385]	-0.0163*** [0.00462]
Population (log)	-0.00237 [0.00557]	-0.0284 [0.0101]	-0.0284 [0.0151]	-0.0284 [0.0186]
Proportion of population with at least a high school education	-0.0372* [0.0202]	-0.106*** [0.0229]	-0.106*** [0.0128]	-0.106*** [0.0352]
Proportion of civilian workforce that is employed	0.0326 [0.0436]	0.0390 [0.0378]	0.0390 [0.0154]	0.0390 [0.0403]
Proportion of population that is African-American	0.00675 [0.0118]	-0.275** [0.0825]	-0.275** [0.0827]	-0.275** [0.109]
Year	0.000976*** [0.000149]	0.00160*** [0.000185]	0.00160*** [0.000122]	0.00160*** [0.000297]
Sum of all local government spending (log)	0.0121* [0.00648]	0.0299** [0.0081]	0.0299** [0.00347]	0.0299** [0.0129]
Number of observations	419	419	419	419
R^2	0.252	0.453	0.453	0.453
Number of states		47	47	47

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Curriculum Vitae

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<u>Education</u>

PhD Health Economics	2012-2017	Johns Hopkins University
MSc Development Studies	2005-2006	University College Dublin
Institute of Actuaries professional exams	1997-2002	Institute of Actuaries, London
Bachelor of Actuarial & Financial Studies	1994-1997	University College Dublin

<u>Experience</u>

Researcher (economics, machine learning), US Mortality Project Jan 2014 – present

Johns Hopkins Bloomberg School of Public Health

Measuring effects of public health spending on mortality using US Census and NVSS mortality data. Application of machine learning methods to the classification of public health expenditure data.

Researcher (demography), Institute for International Programs Jan 2014 - present

Johns Hopkins Bloomberg School of Public Health

Rapid Mortality Monitoring team member (http://collections.plos.org/rmm). Development and testing of new methods of indirect child mortality estimation for countries lacking vital registration systems.

Researcher, Population Family and Reproductive Health Department Sep 2012 - present

Johns Hopkins Bloomberg School of Public Health

A range of projects including fertility and mortality change in developing countries and maternal and child health, TA and guest lectures. Dissertation research focused on geospatial health equity in the US and India.

Maternal & Child Health Research Coordinator May 2012 - Dec 2012

UNICEF Sierra Leone

Led qualitative research as part of a mixed methods investigation into barriers to increasing coverage of maternal and child health interventions. Designed research tools, trained research teams, analysed data and wrote research report for UNICEF NY.

Deputy Country Manager, Innovations for Maternal, Newborn and Child Health

Concern Worldwide, Sierra Leone May 2009 - Apr 2011

Bill & Melinda Gates Foundation funded Maternal and child health evidence-generation multi-country programme. Partnered with Ministry of Health Sierra Leone, planning and launch of Free Healthcare Initiative.

Monitoring & Evaluations Officer, Accelerated Child Survival and Development

UNICEF, Malawi Feb 2007 – May 2009

Coordinated monitoring and evaluation for health section, including national Child Survival and Development strategy, regional UNICEF M&E, global stocktaking team and independent evaluations, UNDAF Child Health sub-cluster. Conducted field monitoring of UNICEF and partners' child health and nutrition programmes.

Product Development Manager Oct 2002 – Jun 2003

AIA, Singapore

Led a team of experienced professionals in the creation of investment and insurance products for competitive financial markets, including negotiation with senior management and national regulators.

Actuarial Specialist Sep 1997 – Sep 2002

Scottish Provident Ireland and Abbey National Insurance, Dublin

Designed mathematical models for insurance and pension products for pricing, reserving and reporting purposes. Conducted economic and financial research and managed the introduction of new systems.

Research

Brady E, Leider JP, Resnick B, Alonso YN, Bishai D (2017) Machine Learning Algorithms to Code State Public Health Spending Accounts. Public Health Reports, forthcoming.

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Sharkey A, E Brady, D Espeut, M Kouletio. A Conceptual Framework for Analyzing Barriers to Coverage of Maternal, Newborn and Child Health Interventions. Concern Worldwide, 2010

<u>Skills & Awards</u>

Software:	R, Stata, SPSS, SAS, ArcGIS, @Risk, Prophet
Languages:	English, Irish, French
Relevant training:	Communications and media interactions, Concern Worldwide, Dublin, 2011
	Evidence based planning to strengthen health systems, World Bank, Rwanda, 2008

Spectrum Lives Saved Tool, Johns Hopkins, Malawi, 2008
Marginal Budgeting for Bottlenecks, UNICEF, Malawi, 2007
Results-based Planning, Monitoring and Evaluation,
AMREF, Kenya, 2007

Academic awards: Sommer Scholarship 2014-2017, Young J. Kim Award for Demography & Population Studies 2015 & 2014, Carl Swan Shultz Award for Demography Studies 2014.